Do We Accept Accrual Profits at Our Peril?
Qiao Liu and Rong Qi

The study described documented evidence that informed traders use their proprietary information on accrual quality to trade against average investors. The informed traders’ arbitrage strategy generated annualized abnormal returns adjusted by size and book-to-market value of 19.8 percent over the 1993–2002 period. The accrual profits were still significant after trading costs were subtracted. The findings suggest that (1) informed traders’ profits from accruals-based strategies derive mainly from their costly information on accrual quality and (2) the persistence of the “accrual anomaly” may be driven by nondiversifiable information risk. The study suggests a strategy for uninformed traders to overcome the information barrier by mimicking informed traders.

One of the most robust market anomalies discussed in recent asset-pricing literature is that stock prices fail to capture the implications of accruals for future earnings (Sloan 1996). It is well documented that investors do not fully understand the differences in persistence of accruals and cash flows; investors tend to overweight accruals and underweight cash flows when forming earnings expectations. As a result, high-accredual companies earn lower abnormal returns than low-accredual companies. A long-standing puzzle in the accrual literature is: Given the economic magnitude (about 10 percent in most studies) of accrual mispricing, why is this “accrual anomaly” not arbitraged away? That is, why would the more sophisticated investors not exploit this opportunity and quickly eliminate accrual mispricing?

A priori, at least two reasons come to mind for expecting informed traders to exploit the accrual mispricing. First, informed investors have incentives to detect the information in accruals and trade on it actively because of the magnitude of the accrual anomaly. Second, informed investors, relative to other investors, are more capable of making refined assessments of earnings quality and better understand the value implications of accruals. Previous studies generated mixed evidence related to these reasons. Bradshaw, Richardson, and Sloan (2001) documented that analysts and auditors do not anticipate the consequences of high accruals. Richardson (2003) showed that short sellers do not systematically trade on accruals. Beneish and Vargus (2002) and Collins, Gong, and Hribar (2003) demonstrated, however, that insiders and institutional investors do profit from accrual mispricing.

We can put aside this inconclusive evidence and focus on the real puzzle here: If informed traders are trading on accruals, why does the accrual anomaly persist? Lev and Nissim (2004) suggested that basing a strategy on accruals might not be attractive to institutional investors because companies with extremely high or extremely low accruals have characteristics institutional investors tend to avoid. Mashruwala, Raigopal, and Shevlin (2004) attributed the persistence of the accrual anomaly to high arbitrage risk.

We believe two principal difficulties are associated with the interpretation of findings in previous studies. First, because informed traders are largely unobservable, previous studies used proxies for informed traders without fully taking into account differences among the proxys. Second, although an accruals-based strategy might be profitable but not implementable because of high trading costs, few previous studies clearly quantified the trading costs of implementing accrual strategies.

We reexamine the size and persistence of the accrual anomaly by investigating whether informed traders can profit from trading on accrual information after explicitly controlling for trading costs. Our research design allowed us to address the two difficulties. First, we did not require ex ante identification of informed traders. Second, we directly estimated the trading costs of implementing accrual strategies.

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Related Literature and Empirical Framework

In the finance literature, three areas are particularly relevant to our study: investigating the accrual anomaly, measuring the extent of informed trading, and estimating the costs of trading.

The Accrual Anomaly. In a seminal work, Sloan (1996) found that investors fail to correctly price the accrual component of earnings. In particular, investors overweight accruals and underweight cash flows. Sloan showed that in the 1962–91 period, a hedge strategy of buying companies with low accruals and selling companies with high accruals earned an average size-adjusted abnormal return of 10.4 percent in the year following portfolio formation. Later research confirmed and expanded Sloan’s finding. Subramanyam (1996), Xie (2001), and Thomas and Zhang (2002), among others, found that specific accruals (e.g., abnormal accruals, inventories) are responsible for the accrual anomaly. The relationship between the accrual anomaly and other anomalies, such as post-earnings-announcement drift (Collins and Hribar 2000) and the value versus growth (or “glamour”) issue (Desai, Rajgopal, and Venkatachalam 2004), has also been investigated.

These efforts have greatly expanded the profession’s understanding of the source and nature of the accrual anomaly. However, a long-standing puzzle remains: Given the relatively simple exploitation strategy of the accrual anomaly, why would sophisticated, well-endowed investors not adopt an accruals-based strategy and quickly dissipate the anomaly? The research so far has generated mixed evidence. Bradshaw et al. (2001) documented that analysts and auditors do not anticipate the consequences of high accruals. Richardson (2003) showed that short sellers do not systematically trade on accruals. Beneish and Vargus (2002) and Collins et al. (2003) found, however, that insiders and institutional investors are able to profit from accrual mispricing.

The persistence of the accrual anomaly, combined with the paucity of evidence that sophisticated investors actually profit from accrual mispricing, makes researchers wonder about the illusory nature of accrual profits. Lev and Nissim (2004) suggested that an accruals-based strategy might not be attractive to institutional investors because companies with extremely high and extremely low accruals have characteristics institutional investors tend to avoid—i.e., small size, low stock price, and low book-to-market ratio (B/M).

Mashruwala et al. (2004) suggested that arbitrage risks impede arbitrageurs from eliminating anomalies in equity markets (see also Shleifer and Vishny 1997; Mitchell, Pulvino, and Stafford 2002).

Does the cost of implementing an accruals-based strategy deter investors? To establish that higher trading costs prevent sophisticated investors from exploiting accrual mispricing, one must demonstrate that informed traders cannot make noticeable abnormal returns in real time. Although previous literature partially achieved this goal, interpretations of the evidence are subject to two caveats. First, prior literature tended to use analysts, auditors, short sellers, institutional investors, or insiders as proxies for informed traders without fully taking into account their disparate incentives, different information-generating and -processing capabilities, and differences in their representation in companies’ investor bases. Second, prior research did not directly address whether informed traders can make profits after subtracting trading costs.

Measuring the Extent of Informed Trading. Easley, Kifer, O’Hara, and Paperman (1996) developed and used the “probability of information-based trading” (PIN) variable to measure the 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. Our model and construction of the PIN measure are as follows.

Three types of players are envisioned in the market 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 sell orders is also ε. Every day, the probability that an information event will occur is α; if it does occur, the probability of bad news is δ and the probability of good news is 1 − δ. 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 − α), 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 αδ), the arrival rate of a buy order will be ε and the arrival rate of a sell order will be ε + μ. On a day with a good information event (with probability α(1 − δ)), the arrival rate of a buy order will be ε + μ and the arrival rate of a sell order will be ε. Let θ = (ε, α, δ, μ).
The likelihood function for a single trading day is given by

\[ L(\theta | B, S) = (1 - \alpha) e^{-\beta} \frac{e^{B}}{B!} e^{-e} \frac{e^{S}}{S!} + \alpha \delta e^{-\beta} \frac{e^{B}}{B!} e^{-e} \frac{(e + \mu)^S}{S!} \]

\[ + \alpha (1 - \delta) e^{-e} \frac{(e + \mu)^B}{B!} e^{-e} \frac{e^{S}}{S!}, \]

where \( B \) is the number of buy orders and \( S \) is the number of sell orders in a single trading day.\(^3\)

Using the number of buy and sell orders in every trading day in a given quarter/year—that is,

\[ M = (B_t, S_t) \]

—and assuming cross-trading-day independence, we estimated the parameters of the model \((e, \alpha, \delta, \mu)\) by maximizing the following likelihood function:

\[ L(\theta | M) = \Pi \, L(\theta | B_t, S_t). \]

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

\[ \text{PIN} = \frac{\alpha \mu}{\alpha \mu + 2e}. \]

We maximized the likelihood function given in Equation 1 for the parameter space \( \theta \) and then calculated PIN for the period 1993–2002 on a quarterly basis. The standard error of PIN was calculated by using the delta method. PIN was thus used in our empirical analysis as a measure of the extent of informed trading.

The PIN measure, by its very construction, captures the probability of information-driven trading, but as an estimated variable, PIN has several shortcomings. First, PIN is potentially subject to an errors-in-variables (EIV) bias. Second, for estimating the PIN measure, the cross-trading-day independence assumption is critical but the existence of stealth trading implies that this assumption is unlikely to be satisfied. (In stealth trading, informed traders camouflage their private information to spread their trades over time; see Barclay and Warner 1993.)

These two shortcomings are unlikely to have much effect on our results, however, because in our empirical analysis, we used PIN only to sort portfolios. The errors in the estimated variables had little effect on which portfolio an individual stock belonged in. Our approach was in the spirit of the portfolio approach used in Fama and French (1992) to correct for the EIV problem in the estimation of beta. Regarding stealth traders, if informed traders do camouflage their private information by spreading their trades, that condition would bias any effect of PIN downward.

**Trading-Cost Estimation.** To assess the profitability of an accruals-based strategy for informed traders, we needed to explicitly estimate trading costs. The empirical literature has generated a set of estimation methods (see, for example, Lesmond, Schill, and Zhou 2004; Ke and Ramalingegowda 2005). To offer a complete picture of how trading costs affect the profitability of an accruals-based strategy, we adopted the three most commonly used methods.\(^4\)

- **Direct effective spread**. We first computed the direct effective spread, DES, by comparing the quoted bid–ask spreads with the contemporaneous execution prices, \( P \). DES is calculated as

\[ \text{DES}_{ij} = \frac{1}{12} \sum_{\tau = -18}^{6} \frac{1}{12} \left( \frac{\text{Ask}_{i,j+\tau} + \text{Bid}_{i,j+\tau}}{P_{i,j+\tau}} \right), \]

where \( \tau \) specifies the month.

Similar to Lesmond et al. (2004), we determined the trading cost of a certain stock as the average of the prior 12 monthly estimates starting 6 months before the actual portfolio formation date. We omitted the few monthly estimates greater than 100 percent to control for the influence of outliers.

A problem with the DES measure is that it captures only the bid–ask spread. Total trading costs, however, include applicable commissions, price impact, taxes, short-sale costs, and other costs of obtaining immediacy. The DES as defined in Equation 5 thus underestimates total trading costs.

- **Limited dependent variable**. Directly controlling for all trading-cost components is necessary but empirically challenging. Lesmond, Ogden, and Trzcinka (1999) proposed a way to estimate total trading costs by using limited dependent variable (LDV) methods.\(^5\) The LDV estimate is a more comprehensive estimate of the cost of trading than the DES measure because LDV implicitly includes not only the spread component but also the implied commissions, immediacy costs, short-sale costs, and some of the price impact. Because the LDV measure is a more comprehensive variable, we used it as our main proxy for trading costs.

However, LDV also has several limitations. Estimates of LDV are based on the assumptions that the underlying true return is normally distributed (whereas the observed or measured return distribution is nonnormal) and that prices respond to information only when the value of the information is greater than the costs of trading. Thus, we included a third method.

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The Wermers method. As our last proxy for trading costs, we applied Wermers’ (2000) method to compute the ex post trading costs (both direct and indirect) incurred by informed traders in each calendar quarter. Specifically, we used the following two equations to estimate the cost of purchasing stock \( i \) during quarter \( t \), \( C^B_{i,t} \), and the cost of selling stock \( i \) during quarter \( t \), \( C^S_{i,t} \):

\[
C^B_{i,t} = 1.098 + 0.092 T r s i z e_{i,t} - 0.084 \ln(mcap_{i,t}) + 13.807 \left( \frac{1}{P_{i,t}} \right), \quad (6a)
\]

and

\[
C^S_{i,t} = 0.979 + 0.214 T r s i z e_{i,t} - 0.059 \ln(mcap_{i,t}) + 6.537 \left( \frac{1}{P_{i,t}} \right), \quad (6b)
\]

where

- \( T r s i z e \) = trade size (the dollar value of the trade divided by the market capitalization of the stock over a calendar quarter)
- \( \ln(mcap) \) = the natural logarithm of market capitalization of the stock (in thousands)

Note that in Equation 6, \( T r s i z e \) controls for the effect of trade size on trading costs and \( \ln(mcap) \) captures the liquidity effect. The inverse of stock price is included because the proportional fixed trading cost is expected to decrease with stock price. Because we cannot observe the size of informed traders’ trades, we chose the 25th percentile of all the trades that occurred in a given quarter and used it as a proxy for the trade size. A weakness of this measure is that it is designed to gauge trading costs for mutual funds. Whether extreme-accrual stocks have some characteristics that make the Wermers method less applicable to them than to mutual funds is not clear, but the results of this measure should be interpreted with caution.

Data and Descriptive Statistics

Our analysis is based on a sample of 9,940 company-year observations consisting of 2,170 companies with December fiscal year-ends and coverage on the CRSP, Compustat, and TAQ (Trade and Quote) databases for 1993-2002. Our initial sample comprised all companies with coverage on TAQ. Following Easley et al. (1996), we confined our estimation of PIN to NYSE and Amex stocks. Using the trade data from TAQ, we estimated a PIN for each company-quarter. The maximum-likelihood algorithm did not converge in all company-quarter regressions, but we were able to obtain 16,561 company-quarter observations with converged estimated parameters.

Panel A of Table 1 presents the descriptive statistics for the set of parameters characterizing informed trading. The summary statistics for these parameters are similar to those identified in previous studies.

In Panel B of Table 1, we provide the summary statistics for all the other variables used in the study. We measured accruals by using the balance sheet method (see Sloan 1996), as follows:

\[
\text{Accruals} = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - \text{Dep},
\]

where

- \( \Delta CA \) = change in current assets (Compustat Item 4)
- \( \Delta Cash \) = change in cash or cash equivalents (Item 1)
- \( \Delta CL \) = change in current liabilities (Item 5)
- \( \Delta STD \) = change in short-term debt included in current liabilities (Item 34)
- \( \Delta TP \) = change in income taxes payable (Item 71)
- \( \text{Dep} \) = depreciation and amortization expense (Item 14)

Following Sloan (1996), we scaled accruals by average total assets (Item 6) and labeled the resultant variable \( ACC \). We then defined \( EARN \) as the income from continuing operations divided by average total assets and \( CFO \) as the difference between \( EARN \) and \( ACC \). And on the basis of a modified Jones (1991) model, we calculated abnormal accruals, \( ABACC \).

For each company-year observation, we chose the PIN measure based on the second quarter’s trade data (from April to June). This is the period during which annual reports are released and informed traders start to form their portfolios. We matched all the companies with coverage on Compustat and CRSP with the PIN measure. We deleted company-year observations if the PIN measure was missing. The sample was further reduced by eliminating (1) financial services companies (SIC codes 6000-6999), (2) companies with non-December fiscal year-ends, (3) companies with insufficient data to compute accruals, (4) companies with total assets less than $1 million, and (5) companies with discontinued operations (Item 66) exceeding 5 percent of total assets. We were left with 9,940 company-year observations in our final sample.

We then computed \( Size \) as the market capitalization (in millions) of each company at the end of year \( t - 1 \) and \( BM \) as the book value of equity divided by its market value at the end of year \( t - 1 \).
Table 1. Descriptive Statistics, 1993–2002

<table>
<thead>
<tr>
<th>Variable</th>
<th>( \alpha )</th>
<th>( \mu )</th>
<th>( \delta )</th>
<th>( \epsilon )</th>
<th>PIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N )</td>
<td>16,561</td>
<td>16,561</td>
<td>16,561</td>
<td>16,561</td>
<td>16,561</td>
</tr>
<tr>
<td>Mean</td>
<td>0.381</td>
<td>46.242</td>
<td>0.404</td>
<td>58.596</td>
<td>0.187</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.197</td>
<td>68.096</td>
<td>0.278</td>
<td>129.73</td>
<td>0.087</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Q1</td>
<td>0.247</td>
<td>8.559</td>
<td>0.178</td>
<td>4.910</td>
<td>0.127</td>
</tr>
<tr>
<td>Median</td>
<td>0.363</td>
<td>20.570</td>
<td>0.364</td>
<td>14.463</td>
<td>0.170</td>
</tr>
<tr>
<td>Q3</td>
<td>0.482</td>
<td>52.767</td>
<td>0.600</td>
<td>49.319</td>
<td>0.227</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.00</td>
<td>707.144</td>
<td>1.00</td>
<td>654.62</td>
<td>0.816</td>
</tr>
</tbody>
</table>

A. Descriptive statistics of information-based trading parameters

B. Descriptive statistics of other variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>ACC</th>
<th>EARN</th>
<th>CFO</th>
<th>ABACC</th>
<th>Size</th>
<th>BM</th>
<th>RAWRET</th>
<th>ABRET</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N )</td>
<td>9,940</td>
<td>9,940</td>
<td>9,940</td>
<td>8,920</td>
<td>16,561</td>
<td>16,561</td>
<td>16,561</td>
<td>16,561</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.039</td>
<td>0.110</td>
<td>0.154</td>
<td>0.003</td>
<td>7.091</td>
<td>0.588</td>
<td>11.09%</td>
<td>-0.18%</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.078</td>
<td>0.247</td>
<td>0.189</td>
<td>0.064</td>
<td>29.607</td>
<td>0.580</td>
<td>43.74%</td>
<td>42.67%</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.626</td>
<td>-0.909</td>
<td>-0.796</td>
<td>-0.624</td>
<td>3.71</td>
<td>0.009</td>
<td>-97.73%</td>
<td>-177.59%</td>
</tr>
<tr>
<td>Q1</td>
<td>-0.074</td>
<td>0.051</td>
<td>0.093</td>
<td>-0.032</td>
<td>456.52</td>
<td>0.307</td>
<td>-11.74%</td>
<td>-21.27%</td>
</tr>
<tr>
<td>Median</td>
<td>-0.042</td>
<td>0.087</td>
<td>0.142</td>
<td>-0.002</td>
<td>1,241</td>
<td>0.505</td>
<td>8.050%</td>
<td>-2.01%</td>
</tr>
<tr>
<td>Q3</td>
<td>-0.008</td>
<td>0.135</td>
<td>0.200</td>
<td>0.027</td>
<td>3,924</td>
<td>0.752</td>
<td>26.797%</td>
<td>15.61%</td>
</tr>
<tr>
<td>Maximum</td>
<td>1.688</td>
<td>7.986</td>
<td>5.797</td>
<td>0.441</td>
<td>845.032</td>
<td>25.540</td>
<td>895.00%</td>
<td>830.00%</td>
</tr>
</tbody>
</table>

Notes: In Panel A, \( \alpha \) is the probability of an information event, \( \mu \) is the arrival rate of information-driven trading for a particular trading day, \( \delta \) is the probability of bad news, and \( \epsilon \) is the arrival rate of noisy trading. PIN is the probability that any trading occurring at time \( t \) is information based. In Panel B, ACC is scaled accruals, EARN is income from continuing operations divided by average total assets, CFO is EARN minus ACC, ABACCs are abnormal accruals, Size is the market capitalization (in millions of dollars) of each company at the end of each fiscal year, RAWRET is one-year-ahead raw buy-and-hold return, and ABRET is the raw buy-and-hold return minus the buy-and-hold return on a size- and B/M-matched value-weighted portfolio of companies.

We formed a one-year-ahead portfolio return on 30 April, which is four months after the fiscal year-end. This arrangement ensured complete dissemination of accounting information in the financial statements of the previous fiscal year (year \( t - 1 \)). RAWRET is the one-year-ahead raw buy-and-hold return, which started to accumulate on 1 May.

To calculate ABRET—the size- and B/M-adjusted abnormal return—we took the raw buy-and-hold return and subtracted the buy-and-hold return on a size- and B/M-matched value-weighted portfolio of companies. We first sorted stocks into deciles based on company size at the end of year \( t - 1 \); we then sorted the stocks within each size decile into quintiles by B/M. Monthly benchmark portfolio returns were then computed as the value-weighted holding-period buy-and-hold return of each portfolio. The benchmark portfolios were reconstituted at the end of each June.

Hedge Portfolio Test. In our context, the hedge portfolio test examined the economic magnitude of accrual mispricing by computing the one-year-ahead returns to various portfolios sorted by accruals and PIN. As in Sloan (1996), we formed portfolios annually by assigning companies to deciles based on total accruals. Within each decile, we further sorted the stocks into three equally sized groups based on PIN. Table 2 reports raw one-year-ahead buy-and-hold returns (RAWRET) and size- and B/M-adjusted abnormal returns (ABRET) to these portfolios.

The second row of Table 2 reports the abnormal return to each accruals-based 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 earned a hedge return of 13.3 percent, higher than Sloan’s reported 10.4 percent. This difference can be accounted for by differences in sample periods and methods of classifying samples.

Rows 3–5 report the size- and B/M-adjusted abnormal returns to the 30 portfolios sorted by both accruals and PIN. The hedge strategy confined to the low-PIN stocks yielded an abnormal return of 9.0 percent. Strikingly, the hedge strategy most likely to be implemented by informed traders—the strategy confined to stocks with a high PIN—yielded an abnormal return of 19.8 percent, which is far larger than those of the sample average and the other two PIN groups.

Can Informed Traders Profit from Accrual Mispricing?

The Mishkin (1983) test and the hedge portfolio test are the two approaches most commonly used to test for accrual mispricing in the accrual literature. Because the Mishkin test does not directly provide information about the economic magnitude of the accrual mispricing, we focus the discussion here on the hedge portfolio test.9

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Figure 1 plots the growth in size- and B/M-adjusted abnormal returns for the whole sample and the three portfolios based on the low, medium, and high PINs. Clearly, the abnormal return to an accruals-based portfolio is driven mainly by the return behavior of the stocks with the highest average PIN.

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

As a check of these results, we also calculated the Sharpe ratios for the various portfolios. We found that the Sharpe ratio for the hedge portfolio with a high PIN was as high as 1.01, which offers a very lucrative investment opportunity that is difficult to forgo.

Robustness Checks. We examine in Table 3 whether our results are robust to various alternative specifications. Because the PIN measure has a significant negative correlation with Size, we first tested whether the results are partially driven by the size effect. Next, because Desai et al. (2004) provided evidence that the accrual anomaly is the glamour (growth) stock phenomenon in disguise, we wondered whether the explanatory power of PIN can be partially attributable to B/M. To address these concerns, we regressed PIN on Size, BM, the leverage ratio, and dummies for year, industry, and stock exchange. The residuals of the PIN regression, which are orthogonal to company size, B/M, and leverage, were retained and used as proxies for the level of informed trading.

For this test, we first sorted stocks into deciles by accruals. We then divided each decile into three equally sized groups based on the residual PIN. We computed the one-year-ahead size- and B/M-adjusted abnormal returns on each portfolio. For brevity, we report the returns to only the two extreme-accrual deciles (D1 and D10). As can be seen in Panel A of Table 3, the hedge strategy (with the long position in the lowest-accrual decile and the short position in the highest-accrual decile) generated an abnormal return of 16.5 percent for the high-residual-PIN stocks. The monotonic pattern in the abnormal stock returns for increasing residual PIN indicates that when informed traders actively trade on the information in accruals, they can earn an abnormal return that cannot be accounted for by either size or the value versus growth effect. Being informed pays off.

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Figure 1. Adjusted Abnormal Returns to Portfolios and Whole Sample from Trading on Accrual Information, Data for 1993–2002

![Graph showing accrual returns over time for different PIN categories.](image-url)

Notes: Period is from the portfolio formation month (Month 1) to one year after the portfolio formation (Month 12). Returns were measured from 1 May through 30 April of the following year.
Table 3. Returns to Portfolios Sorted by Alternative Variables, Data for 1993–2002
(f-statistics in parentheses)

<table>
<thead>
<tr>
<th>A. Classification by accruals and residual PIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residual PIN</td>
</tr>
<tr>
<td>---------------</td>
</tr>
<tr>
<td>Low</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Medium</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>High</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>B. Classification by abnormal accruals (ABACC) and PIN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abnormal Accrual Decile</td>
</tr>
<tr>
<td>--------------------------</td>
</tr>
<tr>
<td>Low</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Medium</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>High</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>C. Classification by accruals and PIN (using four-factor model)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accrual Decile</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>Low</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Medium</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>High</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Notes: Panel A 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 ordinary least-squares regression of PIN against company size, B/M, and the leverage ratio. Panel B reports ABRETS for portfolios sorted by ABACC (abnormal accruals) and PIN. Panel C reports ABRETS for portfolios sorted by PIN and accruals and shows the abnormal stock returns as the intercepts of the four-factor regression model for monthly excess return (Equation 8).

Xie (2001) found that abnormal accruals are less persistent than normal accruals, so the accrual anomaly might be driven by earnings management. As a robustness check, we examined whether informed traders can profit from the trading strategy based on abnormal accruals. We first calculated the abnormal accruals according to the modified Jones (1991) model. We then carried out the two-way classification of stocks by PIN and abnormal accruals. We sorted stocks in our sample into deciles by abnormal accruals and then divided each decile into three equally sized groups by PIN. As shown in Panel B of Table 3, the hedge strategy confined to the high-PIN stocks earned an abnormal return of 19.1 percent. The abnormal returns generated by the strategy based on abnormal accruals were largely accounted for by high-PIN stocks; that is, the informed traders’ trading activity drives the abnormal accrual anomaly.

In our prior analysis, we used the returns to the size- and B/M-matched portfolios as benchmarks to calculate abnormal returns. In this next robustness check, we added the Fama–French four-factor (market, size, B/M, and momentum) model to compute the abnormal returns of the accruals/PIN-based portfolios. This analysis is especially important because we did not control for the momentum effect in prior analyses. For this test, we applied a two-way classification again by using accruals and PIN to sort the stocks into 30 portfolios. We calculated the equal-weighted monthly portfolio returns for each portfolio for the period from 1 May of year $t$ to 30 April of year $t + 1$. We then ran a time-series regression of the monthly portfolio returns against the Fama–French four factors as follows:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1 (R_{m,t} - R_{f,t}) + \beta_2 SMB_i + \beta_3 HML_i + \beta_4 Momentum_i + \epsilon_{i,t},$$

(8)

where $i =$ the portfolio, $R_{i,t} =$ monthly portfolio return in month $t$, $R_{f,t} =$ monthly risk-free rate, and $R_{m,t}, SMB_i, HML_i$, and $Momentum_i$ capture, respectively, the effects of the market factor, the size factor (small minus big), the B/M factor (high B/M minus low B/M), and the momentum factor in month $t$. The intercept from the regression, $\alpha_i$, represents the abnormal monthly return generated by holding portfolio $i$. Multiplying $\alpha_i$ by 12 provided the annualized abnormal return to portfolio $i$.

Panel C of Table 3 shows the results of using this test. Again, for expositional reasons, we report only the abnormal returns for the extreme-accrual deciles. The hedge strategy confined to the high-PIN stocks earned an abnormal return of 17.8 percent. The positive returns to the hedge strategies shown in Panel C imply that after market, size, B/M, and momentum effects are controlled for, informed traders can still earn an abnormal return of 7.4–17.8 percent by trading on accrual information.

Are Accrual Profits Real? We have demonstrated that informed traders are able to earn an annualized abnormal return close to 20 percent by trading on accruals (or abnormal accruals). The
question is whether such accrual profits are real for informed traders after trading costs are taken into account. Extreme-accrual stocks have been found to have higher arbitrage costs than other stocks (Mashruwala et al. 2004) and have unpopular characteristics that arbitrageurs tend to avoid (Lev and Nissim 2004). Is the persistence of the accrual anomaly a result of the costs of implementing an accruals-based strategy?

To address this question, we used three methods of estimating trading costs. Because equal weighting was used in computing the returns to various portfolios, we also equal-weighted trading costs. Our trading-cost estimates represent the mean round-trip cost for trading a stock in the various portfolios. We computed trading costs for two scenarios: (1) trading costs based on 100 percent turnover (that is, the positions would be closed at the end of the holding period) and (2) trading costs based on actual turnover. In the second scenario, we took into consideration that some stocks in the extreme-accruals/PIN deciles would remain in the same portfolios from one holding period to another. Thus, informed traders would not need to close out all positions. For example, if a stock was in the high-PIN/highest-accruals portfolio in the previous period and remained in that portfolio in the next period, investors following the high-PIN/highest-accruals strategy would not close out that stock and re-sort. The trading costs in the second scenario obviously are lower than those in the first scenario but probably reflect actual trading costs incurred.

We calculated the mean proportion of stocks in the high-PIN/lowest-accruals portfolio and high-PIN/highest-accruals portfolio that remained in those portfolios for the next holding period and report the results in the first row of Table 4. When executing the accruals-based strategy, the informed trader can save 38.1 percent of the cost in the short position and 39.6 percent of the cost in the long position by holding the positions in those stocks and carrying them into the next period.

To calculate trading costs in the two scenarios, we computed the direct effective spread, DES, based on Equation 5. The trading cost of a stock was computed as the average of the prior 12 monthly estimates starting 6 months before the actual portfolio formation date. The mean DES for the high-PIN/lowest-accruals portfolio for 100 percent turnover, as shown in Table 4, is 3.49 percent, and the mean DES for the high-PIN/highest-accruals portfolio is 2.86 percent. Therefore, the total round-trip cost of implementing a hedge strategy based on 100 percent turnover is 6.35 percent. The total round-trip cost for actual turnover is 3.88 percent. The profits after trading costs derived from investing in the hedge portfolio by the informed traders are thus 13.46 percent in the first scenario and 15.93 percent in the second scenario.

In using LDV as a proxy for trading costs, for each stock in the portfolios, we estimated \( \alpha_1(i) \) and \( \alpha_2(i) \) on the basis of return data during the prior 12 months starting 6 months before the portfolio formation date. We then calculated the equal-weighted trading costs for the portfolios.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Hedge Return</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Accrual Decile (high PIN only) Based on Size and BM Adjusted for Four-Factor</td>
</tr>
<tr>
<td></td>
<td>D1</td>
</tr>
<tr>
<td>100% turnover DES</td>
<td>3.49%</td>
</tr>
<tr>
<td>LDV</td>
<td>4.56</td>
</tr>
<tr>
<td>WTC</td>
<td>1.73</td>
</tr>
<tr>
<td>Actual turnover DES</td>
<td>2.11%</td>
</tr>
<tr>
<td>LDV</td>
<td>2.75</td>
</tr>
<tr>
<td>WTC</td>
<td>1.04</td>
</tr>
</tbody>
</table>

Note: Returns are one-year-ahead benchmark-adjusted abnormal returns and trading-cost estimates associated with portfolios sorted by ACC and PIN.
As shown in Table 4, the mean LDV estimate for the high-PIN/lowest-accruals portfolio and for the high-PIN/highest-accruals portfolio are both higher than their corresponding DES measures of costs. Based on these (indirect) LDV estimates, the profitability of the accruals-based strategy for informed traders in the hedge strategy after trading costs with 100 percent turnover would be 8.54 percent and with actual turnover, 12.91 percent. Accrual profits after trading costs are thus still lucrative for informed traders.

Finally, we used the method proposed by Wermers (2000) to estimate trading costs (called WTC in Table 4). For each stock, we calculated the costs of buying and selling, \( C^b_{i,t} \) and \( C^s_{i,t} \), on the basis of the trading information and company-specific information in the fourth quarter of year \( t - 1 \). We assumed the trade size to be the 25th percentile of the size of the trades that occurred in that quarter.\(^{10}\)

Table 4 shows the mean cost estimates to be much lower than for either the DES or LDV method. And based on these cost measures, the average abnormal returns for informed traders after trading costs are more substantial than returns calculated by the other methods.

The last columns in Table 4 report abnormal returns after trading costs adjusted for the Fama–French four factors. Because the hedge returns based on the four-factor model are slightly smaller than those for the size- and B/M-adjusted portfolios, Table 4 shows slightly smaller hedge returns after trading costs. But they still offer attractive opportunities to informed traders.

Our findings are consistent with several prior studies. Francis, LaFond, Olsson, and Schipper (2005) proposed that what is systematically priced by the market is not the accrual level but the quality of accruals. The level of accruals becomes public information after the annual reports are released, but their quality remains uncertain. According to Francis et al.:

> Accrual quality tells investors about the mapping of accounting earnings into cash flows. Relatively poor accrual quality weakens this mapping, therefore, increases information risk. (p. 296)

Uncovering a company’s accrual quality is costly. Such costs are nondiversifiable and may impede individual investors from trading on accruals. The persistence of the accrual anomaly, therefore, may be largely accounted for by nondiversifiable information risk rather than trading costs or higher arbitrage risk.\(^{11}\)

### Mimicking Informed Traders

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

PIN is, however, highly autocorrelated. We found that the PIN in year \( t - 1 \) is significantly correlated, at 0.56, with the PIN in year \( t \). Although what accounts for such a high autocorrelation in PIN is unclear, the persistence of PIN allows us to design a trading strategy for average investors that is based on our findings.\(^{12}\) Specifically, uninformed investors can mimic informed investors’ accruals-based trading strategy. Instead of using contemporaneous PIN to sort stocks, an uninformed investor can estimate PIN from the trades in year \( t - 1 \) (which we can consider lagged PIN, or LPIN).

To test whether this strategy is implementable in real time, we replicated our prior analysis but used LPIN. We carried out a two-way classification to sort our sample stocks by LPIN and accruals into 30 portfolios. We applied the hedge portfolio test and report the results in Table 5. As shown, the hedge portfolio with long positions in high-LPIN/lowest-accruals stocks and short positions in high-LPIN/highest-accruals stocks earned an average size- and B/M-adjusted abnormal return (ABRET) of 18.7 percent. This ex ante trading strategy based on LPIN and accruals generated an abnormal return that is similar in magnitude to that of using a contemporaneous PIN (the 19.8 percent given in Table 2). Clearly, uninformed investors, even individual investors, can overcome the information barrier and mimic the trading behavior of informed traders by computing LPIN based on historical data.

### Conclusion

We showed that the hedge returns to the accruals-based strategy first documented by Sloan (1996) are much larger for stocks with the higher levels of information-based trading (higher PINs). We interpret this finding as evidence that informed traders use their proprietary information about the quality of accruals to trade against average investors. Therefore, the larger amount of abnormal returns that informed traders obtain reflects the value of information that is not accessible to everyone.

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We used three methods to calculate the trading costs of implementing accruals-based strategies. We found that informed traders are still able to obtain a sizable abnormal return from an accruals-based strategy after trading costs. Therefore, our findings indicate that the persistence of the accrual anomaly is unlikely to be driven by higher trading costs or arbitrage costs. Non-observable information risk seems to explain the persistence of the accrual anomaly.

Finally, because of the high autocorrelation in PIN, we designed a trading strategy for uninformed investors to mimic the informed traders' strategy. We found that such a mimicking strategy works well and generates accrual profits similar to those available to informed traders.

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This article qualifies for 1 PD credit.

Appendix A. The LDV Estimate

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

\[
\begin{align*}
R(i,t) &= R(i,t)^* - \alpha_1(i) \text{ if } R(i,t)^* \leq \alpha_1(i), \\
R(i,t) &= 0 \text{ if } \alpha_1(i) \leq R(i,t)^* \leq \alpha_2(i), \\
R(i,t) &= R(i,t)^* - \alpha_2(i) \text{ if } R(i,t)^* \geq \alpha_2(i),
\end{align*}
\]  

(A1)

where

\[
\begin{align*}
R(i,t) &= \text{measured return from CRSP} \\
R(i,t)^* &= \text{unobserved return in a frictionless market} \\
\alpha_1(i) &\leq 0 = \text{seller's trading cost for stock } i \\
\alpha_2(i) &\geq 0 = \text{buyer's trading cost for stock } i
\end{align*}
\]

The informed trader's reserved return from trades, \(R(i,t)^*\), is bounded by the applicable trading costs, \(\alpha_1(i)\) and \(\alpha_2(i)\). If trading costs are sizable, according to Lesmond et al. (2004), zero-return days occur more frequently because new information must accumulate longer, on average, before arbitrage capital affects prices. As a result, securities with low trading costs experience few zero returns and securities with high costs experience more zero returns.

Using the common market model \([R(i,t)^* = \beta(i)R_M(t) + e(i,t)]\), where \(R_M(t)\) is the measured CRSP daily return on the market index and \(e(i,t)\) captures all other information, stock returns \(\alpha_1(i)\) and \(\alpha_2(i)\) for a given stock year can be obtained by maximizing the following log-likelihood function:

\[
\ln L = \sum_{R1} \ln \left(\frac{1}{(2\pi\delta_{i1}^2)^{1/2}} \right) - \sum_{R2} \ln \left(\frac{1}{(2\pi\delta_{i2}^2)^{1/2}} \right) \\
\times \left[R(i,t) + \alpha_1(i) - \beta(i)R_M(t)\right]^2 \\
+ \sum_{R2} \ln \left(\frac{1}{(2\pi\delta_{i1}^2)^{1/2}} \right) - \sum_{R1} \left(\frac{1}{2}\delta_{i1}^2 \right) \\
\times \left[R(i,t) + \alpha_2(i) - \beta(i)R_M(t)\right]^2 \\
+ \sum_{R0} \ln [\Phi_2(i) - \Phi_1(i)],
\]

(A2)

where \(R1\) and \(R2\) denote the region where measured return \(R(i,t)\) is located within, respectively; the non-zero negative region and the positive region and \(R_M(t)\) is the return to the market portfolio on day \(t\). Parameter \(\beta(i)\) represents market risk beta, parameter \(\sigma_i^2\) represents the variance of the nonzero observed returns, and \(\Phi(i)\) is the distribution function of the standard normal distribution. The first term corresponds to the negative market returns and the second term corresponds to the positive market returns of Equation A1. 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 \(i\) as \(\alpha_2(i) - \alpha_1(i)\). We call this difference "the LDV measure." Because it is an estimate of investors' reserved returns, it is relatively comprehensive.13
Notes

1. The literature offers two primary explanations for this "accrual anomaly": (1) The relationship between a company's accrual-generating process and future earnings is so complex that investors fail to identify the transitory nature of the accruals (see Sloan 1996), or (2) earnings have been managed opportunistically and investors fail to recognize the low persistence of accruals (see, for example, Teoh, Welch, and Wong 1998a, 1998b; Xie 2001; Ali, Hwang, and Trombley 2001).

2. In their study of the book-to-market anomaly, Ali, Hwang, and Trombley (2003) showed that high arbitrage risk deters arbitrage activity and is an important reason the B/M effect exists. However, whether the same explanation can be applied to the accrual anomaly is not clear. Mashruwala et al. (2004) offered similar evidence on the accrual anomaly. They computed the arbitrage risk as the residual variance from the regression based on the asset-pricing model and showed that high arbitrage risk discourages informed traders from exploiting the arbitrage opportunity. None of them, however, directly estimated the trading costs of implementing arbitrage strategies.

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

4. For each of the estimators, we used a sample period that preceded the portfolio formation period to estimate the trading costs. The aim was to avoid contamination, either distributional or causal, between portfolio formation and performance returns.

5. We discuss in detail in Appendix A how we estimated the LDV measure.

6. Because our sample contained no NASDAQ stocks and the sample period was 1993-2002, we could use a simpler model than the ones used in Wermers (2000).

7. Barclay and Warner (1993) showed that informed traders tend to camouflage their private information and breakdown large trades into medium-sized ones. As a result, the medium-sized trades drive the majority of stock price movements. When we used the median of all trade sizes in a given quarter as a proxy for trade size, we found results quite similar to those reported here.

8. We also used the PIN estimated on the basis of the first quarter's trade data as an alternative. Using it to sort stocks yielded the same qualitative results as reported here, although the abnormal returns generated by an accruals-based strategy were generally 80–100 bps lower.

9. In unreported analysis, we applied the Mishkin test and found strong evidence that accrual mispricing is more pronounced in the stocks with higher PINs. The results are available on request.

10. Assuming the trade size to be the 50th percentile, 10th percentile, or 5th percentile of the size of the trades in that quarter yielded trading costs at different levels, but none of them would change our conclusions.

11. Zhang (2006) showed that information uncertainty helps to explain price continuation anomalies. He defined 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" (p. 105).

12. The reason for the high autocorrelation in PIN may be that informed traders are attracted to companies with certain characteristics and the characteristics do not change much over time.


References


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