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Momentum and Informed Trading

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Abstract

Consistent with the predictions of Wang (1994), we document that firm-specific informed trading is an important determinant of price momentum. The stronger return continuation in stocks with more informed trading cannot be explained by cross-sectional differences in uncertainty proxies such as analyst forecast dispersion, analyst coverage, idiosyncratic return volatility, and size. The relationship between informed trading and return continuation is also not attributable to cross-sectional differences in liquidity. Instead, our evidence emphasizes the role of price discovery in generating short-term price momentum.

JEL Codes: G10, G11

Keywords: Momentum, Informed Trading, Liquidity, Uncertainty

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The returns from momentum strategies, as documented in Jegadeesh and Titman (1993) and again by Jegadeesh and Titman (2001), pose a serious challenge to market efficiency. The robustness of these strategies is confirmed by numerous studies such as Rouwenhorst (1998) and Griffin, Ji, and Martin (2003) that document momentum in international markets. Fama and French (1993) find market, value, and size factors cannot account for momentum returns, while Grundy and Martin (2001) report that firm-specific factors are responsible for momentum.

We examine the relationship between informed trading and price momentum. O'Hara (2003) argues that anomalies such as momentum highlight the need to incorporate informed trading into asset pricing. Our analysis is motivated by Wang (1994)'s price discovery model with heterogeneous investors and asymmetric information. In Wang (1994), informed investors trade either because of their private information or changes in their investment opportunities that cause them to initiate uninformed trades. These distinct motives yield different return dynamics. However, from the perspective of uninformed investors, the motives of informed investors are unpredictable and cannot immediately be identified. Instead, learning allows uninformed investors to eventually correct their initial assessments regarding the extent to which private information is responsible for turnover. When uninformed investors ascertain the presence of private information, they update their cashflow expectations and consequently imitate the earlier trades of informed investors. Thus, provided turnover is motivated by private information, uninformed investors gradually become informed and influence prices in a manner that causes return continuation. Conversely, in the absence of private information, turnover leads to subsequent reversals. These temporary price impacts compensate uniformed investors for the provision of liquidity.[1] Therefore, return continuation in Wang (1994) requires asymmetric information.

We measure asymmetric information using the *probability of informed trading* (PIN) in Easley, Hvidkjaer, and O'Hara (2002). PIN has been utilized extensively as a measure for informed trading, with the next section providing a detailed summary of its estimation and previous empirical applications. Recently, Ferreira and Laux (2007) confirm that firms with better corporate governance have more informative stock prices using the PIN estimates in Easley, Hvidkjaer, and O'Hara (2002). PIN is also well suited for testing the predictions of Wang (1994). In the PIN methodology, good private information causes informed investors to initiate buy trades while

[1]This compensation accounts for the likelihood of trading against private information. However, a risk premium for informed trading is insufficient to generate return continuation.

bad private information causes them to initiate sell trades. The buy and sell imbalances arising from private information increase PIN. Conversely, uninformed trades lower PIN.

We document a strong cross-sectional relationship between return continuation and informed trading using the PIN estimates in Easley, Hvidkjaer, and O'Hara (2002). This relationship is studied using individual stocks returns during several non-overlapping horizons, including an *intermediate* horizon over the prior twelve months (excluding the most recent month). This intermediate horizon corresponds to the formation period of momentum strategies.[2] Our cross-sectional regressions incorporate a firm-specific interaction variable defined by PIN and past returns over the intermediate horizon. This interaction variable predicts future returns in every regression specification. Moreover, the predictability associated with past intermediate returns is eliminated by the introduction of the PIN interaction variable.

As predicted by Wang (1994), the high turnover stocks exhibiting return continuation are those with high PIN. In contrast, high turnover stocks with low PIN exhibit return reversals. Intuitively, uninformed investors are more likely to learn that turnover is being motivated by private information in high PIN stocks. This learning generates return continuation as uninformed investors update their cashflow expectations and imitate the earlier trades of informed investors. Conversely, private information is less likely to be motivating turnover in low PIN stocks. With less informed trading, high turnover leads to subsequent return reversals. Avramov, Chordia, and Goyal (2006) also conclude that return reversals are attributable to liquidity shocks. Their evidence on weekly return reversals indicates that the price impact of uninformed trades has a shorter duration than the monthly horizons in our empirical study.[3]

As reported in Zhang (2006), firm characteristics that proxy for uncertainty such as size and analyst coverage are negatively related to momentum returns, while analyst forecast dispersion and return volatility are positively related to momentum returns. Zhang (2006) interprets these associations as evidence that behavioral biases influence stock prices after assuming that limits to arbitrage are greater in stocks with higher uncertainty. However, including size, analyst coverage,

[2]We study return continuation in individual stocks using cross-sectional regressions as well as the returns from zero-cost momentum trading strategies using double-sorted portfolios.

[3]Llorente, Michaely, Saar, and Wang (2002) document that periods of intense trading activity result in daily return continuation for stocks with high informed trading. However, our study focuses on monthly horizons and controls for uncertainty and liquidity characteristics in the existing momentum literature.

analyst forecast dispersion, and idiosyncratic return volatility in our cross-sectional regressions does not alter the relationship between PIN and return continuation. Furthermore, our results provide stronger support for Wang (1994)'s explanation of return continuation than behavioral biases. Despite exhibiting stronger short-term momentum, high PIN stocks have weaker long-term return reversals. This evidence indicates that an overreaction to private information is not responsible for short-term price momentum.

More generally, behavioral finance relies on limits to arbitrage to prevent arbitrageurs from eliminating mispricings caused by investor psychology. Shleifer and Vishny (1997) argue these limits originate from the risk posed by noise traders. In contrast, we report stronger momentum in high PIN stocks that, by definition, have lower noise trader risk. Moreover, the uncertainty proxies are related to informed trading. Aslan, Easley, Hvidkjaer, and O'Hara (2007) report that size and analyst coverage are negatively related to PIN. Barron, Kim, Lim, and Stevens (1998) attribute a portion of analyst forecast dispersion to disagreement arising from private information, while Wang (1993) demonstrates that asymmetric information increases return volatility. Thus, the association between greater uncertainty and stronger momentum is compatible with informed trading being the origin of return continuation.

Several studies conclude that momentum strategies involve stocks with high transaction costs (Grundy and Martin (2001), Lesmond, Schill, and Zhou (2003), as well as Korajczyk and Sadka (2004)). Nonetheless, the relationship between PIN and return continuation remains after including effective spreads and estimates for Kyle (1985)'s lambda in our cross-sectional regressions. Furthermore, wider effective spreads and larger price impacts arise from increases in asymmetric information. Consequently, by increasing the transaction costs confronting arbitrageurs, informed trading offers a potential explanation for momentum's persistence.[4] Keim (2003) reports that institutional transaction costs are higher for momentum investors than value investors and diversified investors.

For emphasis, our intention is not to dispute the importance of uncertainty and liquidity to momentum returns. Instead, we complement prior findings by offering an alternative interpretation for their importance. Our interpretation recognizes the commonality between proxies for informed trading, uncertainty, and liquidity. Furthermore, by appealing to Wang (1994), the

[4] This paper focuses on the ability of informed trading to explain the existence of momentum returns before transaction costs.

interaction between informed trading and turnover guides our interpretation.

As a robustness test, we regress PIN on the complete set of uncertainty and liquidity proxies as well as order flow imbalances during the holding period. The residuals from this cross-sectional regression represent residual probabilities of informed trading (RPIN) that are independent of the other firm characteristics. These RPIN estimates confirm that the relationship between informed trading and return continuation is not attributable to cross-sectional differences in uncertainty, liquidity, and order flow imbalances.

To complement the cross-sectional regressions and explicitly study their implications for momentum returns, double-sorted portfolios are constructed that first sort firms according to an uncertainty, liquidity, or order flow imbalance characteristic. The second sort creates PIN portfolios within each of the individual firm characteristic portfolios. Momentum returns across these double-sorted portfolios consistently increase with informed trading. Indeed, momentum returns are insignificant in the low PIN portfolio and significant in the high PIN portfolio, irrespective of the firm characteristic in the first sort. Double-sorted portfolios also confirm that a combination of high turnover and high informed trading produces the strongest momentum.

The remainder of this paper begins in Section I by detailing the data used in our empirical tests. Section II then presents our empirical evidence regarding the importance of informed trading to return continuation, while the relationship between informed trading and momentum is examined in Section III. The economic implications of time variation in informed trading is examined in Section IV. The interpretation of our empirical results is contained in Section V, with our conclusions following in Section VI.

I Data and Summary Statistics

We measure informed trading using the probability of informed trading (PIN) estimates in Easley, Hvidkjaer, and O'Hara (2002). This metric originates from order flow data and represents the percentage of trades initiated by informed investors. Intuitively, informed investors are responsible for buy and sell imbalances, which originate from good and bad private information respectively. More formally, each trading day has either good, bad, or no private information. This classification requires two parameters. The first parameter denotes the probability of private information, while the second parameter denotes the probability that this private information is bad (good). These probabilities are estimated from the frequency of large daily order flow imbalances since private information leads to buy and sell imbalances on days with good and bad private information respectively. These informed buy and sell orders are executed with the same intensity. Conversely, uninformed buy and sell orders arrive with different intensities, and are not attributable to private information. A maximum likelihood procedure estimates the five required parameters (two probabilities and three intensities) from the number of daily buy and sell trades.

The likelihood function underlying the estimation of PIN is a mixture of three distributions, each corresponding to a different type of trading day (good, bad, or no private information). The probability of informed trading is then defined as a ratio whose numerator equals the probability of private information multiplied by the intensity of informed trading. This product also appears in the ratio's denominator along with the buy and sell intensities of uninformed trades. Therefore, PIN measures the *relative* amount of informed trading.

The ability of PIN to measure informed trading is confirmed in several studies. Easley, Kiefer, and O'Hara (1996) modify PIN to allow trades to be routed through either the NYSE or the Cincinnati Stock Exchange. This modified PIN indicates significantly more informed trading on the NYSE since uninformed order flow is purchased and executed in Cincinnati. A simpler version of PIN enables Easley, Kiefer, O'Hara, and Paperman (1996) to study infrequently traded stocks by restricting the buy and sell intensities of uninformed investors to be equal. Although PIN and spreads are derived from order flow and prices respectively, this four parameter version of PIN predicts spreads. Easley, Kiefer, and O'Hara (1997) extend PIN to distinguish between small and large trades. They find that trade size is not highly informative, a property that reinforces the appropriateness of the PIN specification in Easley, Hvidkjaer, and O'Hara (2002).

Our primary sample consists of NYSE/AMEX/NASDAQ stocks with available PIN estimates, starting from January 1983 and ending in December 2001. This PIN dataset is then merged with CRSP. Throughout this sample period, an average of 2,191 firms have annual PIN estimates. Extending the PIN dataset beyond 2001 is complicated by the classification of trades as buyer-initiated versus seller-initiated since narrower spreads can compromise the accuracy of the Lee and Ready (1991) algorithm.

A. Uncertainty and Liquidity

The momentum literature has examined the contribution of uncertainty to momentum returns. Jiang, Lee, and Zhang (2005) as well as Zhang (2006) argue that limits to arbitrage are more severe in stocks with greater cashflow uncertainty. These authors presume that larger analyst forecast dispersion and higher idiosyncratic return volatility signify greater uncertainty. Small stocks and those with less analyst coverage are also assumed to have more uncertain future cash-flows. Therefore, when evaluating the marginal contribution of PIN to momentum, we control for size, analyst coverage, analyst forecast dispersion, and return R^2. These four uncertainty proxies are computed each month although they are highly persistent.

Analyst forecast dispersion and analyst coverage are obtained from the IBES database. Analyst coverage equals the number of analysts covering the stock each month, while analyst forecast dispersion is defined as the monthly standard deviation of analysts' earnings forecasts for the next fiscal year divided by the stock price. As in prior empirical studies, we estimate a stock's return R^2 by regressing its weekly return on the return of its industry and the market. Industries are classified according to the 48 categories available on Kenneth French's website. This regression utilizes weekly returns over the past 52 weeks, where these returns are defined as the compounded daily returns between two consecutive Wednesdays.

Pástor and Stambaugh (2003) demonstrate the ability of systematic liquidity fluctuations to capture variation in momentum returns. To ensure that our results regarding informed trading and momentum are not attributable to cross-sectional differences in liquidity, we consider two liquidity characteristics. The first proxy consists of a linear price-impact coefficient, which parallels Kyle (1985)'s lambda over the January 1989 to December 2001 horizon, while the second proxy is the effective spread. The effective spread and Kyle (1985)'s lambda are estimated from transaction and quote data (TAQ). The effective spread equals twice the absolute difference between a trade's execution price and the prevailing midquote divided by this midquote. To estimate lambda, buy and sell orders are aggregated at the daily level to obtain firm-specific order flow imbalances after classifying trades using the Lee and Ready (1991) algorithm. The lambda proxy is estimated as the coefficient from regressing daily stock returns on these daily imbalances. As with the effective spread, these estimated regression coefficients are averaged across each calendar year.[5]

B. Summary Statistics

Table I contains averages and correlations for the firm characteristics in our study. Panel A reports these averages across five PIN quintiles, with P1 denoting the low PIN portfolio and P5 denoting the high PIN portfolio. Panel B records the annual correlations between the firm characteristics.

Consistent with Aslan, Easley, Hvidkjaer, and O'Hara (2007), informed trading is more prevalent in small stocks and stocks with less analyst coverage, while the inverse relationship between return R^2 and PIN implies that stocks with a lower return R^2 have more informative prices.[6] Larger analyst forecast dispersions in high PIN stocks is consistent with Barron, Kim, Lim, and Stevens (1998)'s decomposition of analyst forecast dispersion into uncertainty and disagreement components, with the latter arising from private information.

In contrast to size, analyst coverage, analyst forecast dispersion, and the effective spread, PIN is estimated with error. Nonetheless, asymmetric information is capable of unifying several prior empirical regularities regarding momentum since higher uncertainty and lower liquidity both coincide with greater informed trading. Although there is no pattern in turnover across the PIN portfolios, the next section examines the interaction between PIN and turnover in detail.

The time series standard deviation of the PIN estimates for individual firms averages 0.05 over the sample period, in comparison to the average PIN estimate of 0.22. Furthermore, the average autocorrelation in the PIN estimates equals 0.27. The economic implications of predictability in informed trading is examined in Section IV. Variables such as size and analyst coverage exhibit less time series variation and are more persistent.

[5]Replacing lambda with Amihud (2002)'s price-impact measure yields similar unreported results. The illiquidity measure in Amihud (2002) does not involve transactions data since this ratio is defined as a firm's absolute daily return divided by its corresponding dollar-denominated turnover.

[6]In the absence of asymmetric information, Peng, and Xiong (2006) argue that a low return R^2 (high idiosyncratic volatility) signifies overconfidence. However, Morck, Yeung, and Yu (2000), Durnev, Morck, Yeung, and Zarowin (2003), as well as Li and Myers (2005) conclude that firms with a low return R^2's have more informative prices since their returns are less correlated with those of the market and their industry.

II Informed Trading and Return Continuation

The importance of informed trading to return continuation is evaluated using an interaction variable. This variable is defined as the product of PIN estimates with past returns over an intermediate horizon corresponding to the formation period of momentum strategies. Several specifications of the following Fama-MacBeth (1973) regression involving monthly individual stock returns are estimated

$$\begin{aligned} r_{i,t} \;=\; & \beta_0 + \beta_1 \ln(\text{Size})_{i,t-1} + \beta_2 \text{BM}_{i,t-1} + \beta_3\, r_{i,t-1,t} + \beta_4\, r_{i,t-12,t-2} + \beta_5\, r_{i,t-60,t-13} \\ & + \beta_6 \left[\text{PIN}_{i,t^*} \cdot r_{i,t-12,t-2}\right] + \beta_7 \left[\text{Disp}_{i,t-1} \cdot r_{i,t-12,t-2}\right] + \beta_8 \left[\text{Lambda}_{i,t^*} \cdot r_{i,t-12,t-2}\right] + \epsilon_{i,t}\,, \end{aligned} \tag{1}$$

where ϵ_t is a mean-zero error term and t^* denotes the calendar year containing month t. The $r_{t-1,t}$ and $r_{t-60,t-13}$ variables account for short-term (prior month) and long-term return reversals respectively. The interaction with intermediate past returns denoted $r_{t-12,t-2}$ is required for PIN, forecast dispersion (Disp), and lambda to capture the return continuation associated with momentum.[7]

A firm's market capitalization is measured each month to provide the size and book-to-market (BM) variables. Equation (1) uses analyst forecast dispersion in month $t-1$ although the results are nearly identical with month t values due to its persistence. Furthermore, our conclusions are unchanged if forecast dispersion and lambda are replaced with other uncertainty proxies (analyst coverage or return R^2) and the effective spread respectively. Additional interaction variables induce multicollinearity given their common dependence on past returns over the intermediate horizon. We simultaneously account for the effects of multiple uncertainty and liquidity characteristics later in this section.

Recall that PIN, along with lambda and the effective spread, are estimated over annual calendar-time horizons. Thus, PIN_{t^*} is often estimated over time intervals that overlap with past intermediate returns. This overlap is inconsequential to our cross-sectional analysis, although PIN estimates from the prior calendar year are investigated in Section IV to assess the learning motivation in Wang (1994).[8]

[7]Regressing future returns on PIN is closer to Easley, Hvidkjaer, and O'Hara (2002)'s study regarding a risk premium for informed trading.

[8]As emphasized in Section IV, there is no attempt to formulate a viable trading trading strategy when testing a learning model.

The different specifications of equation (1) are estimated by omitting one or more of the last three variables corresponding to the β_6, β_7, and β_8 coefficients. These specifications enable us to examine the importance of informed trading to return continuation after accounting for analyst forecast dispersion and lambda.

The estimated coefficients from equation (1) are recorded in Table II. In all specifications, the β_1 coefficient for size and β_2 coefficient for book-to-market are insignificant after controlling for past returns. For emphasis, regression coefficients involving the *entire* cross-section of returns and firm characteristics, as in equation (1), differ from the loadings on factor returns. Returns from book-to-market, size, and liquidity factors are utilized in the next section to risk-adjust momentum returns.

Model 1 reveals a positive β_4 coefficient of 0.0063 (t-statistic of 2.16) for $r_{t-12,t-2}$. Thus, past returns over intermediate horizons predict future returns. Conversely, the β_3 and β_5 coefficients are both negative, which is consistent with return reversals over the short-term (prior month) and long-term respectively, although β_5 is insignificant in every specification.

More importantly, in model 2, the interaction variable involving informed trading has a significant β_6 coefficient of 0.0895 (t-statistic of 3.60) that renders the β_4 coefficient for $r_{t-12,t-2}$ insignificant (t-statistic of -1.42). Thus, the *interaction* between informed trading and past intermediate returns is responsible for return continuation. Indeed, the β_4 coefficient for past intermediate returns is insignificant (and negative) in every specification that includes the $\text{PIN}_{t^*} \cdot r_{t-12,t-2}$ interaction variable.

The economic significance of the β_6 coefficient can be interpreted by considering a change in PIN. Conditional on $r_{t-12,t-2}$, an increase in PIN by 0.01 increases returns in the holding period by $\beta_6 \cdot 0.01$. With the average β_6 coefficient in Table II being slightly below 0.10, every 0.01 increase in PIN implies the monthly holding period return is $0.001 \cdot r_{t-12,t-2}$ higher, which implies an annual increase exceeding $0.01 \cdot r_{t-12,t-2}$. Recall that the standard deviation of PIN, at the individual firm level, averages 0.05. Thus, a two standard deviation increase in PIN increases annual holding period returns by more than 10% of the formation period's return.

Models 3 and 4 indicate that the interaction variables involving analyst dispersion and lambda have insignificant β_7 and β_8 coefficients. Therefore, after controlling for past returns, uncertainty and liquidity cannot explain return continuation. Instead, the significant β_6 coefficients in models 5, 6, and 7 for the $\text{PIN}_{t^*} \cdot r_{t-12,t-2}$ interaction variable confirm the importance of informed trading to return continuation.

A. Turnover

In Wang (1994), a combination of informed trading and high turnover produces return continuation. Without informed trading, high turnover induces a liquidity shock that subsequently leads to return reversals rather than return continuation. To investigate these empirical predictions, we perform the following cross-sectional regression

$$\begin{aligned} r_{i,t} &= \beta_0 + \beta_1 \ln(\text{Size})_{i,t-1} + \beta_2 \text{BM}_{i,t-1} + \beta_3\, r_{i,t-1,t} + \beta_4\, r_{i,t-12,t-2} + \beta_5\, r_{i,t-60,t-13} \\ &\quad + \beta_6\, [\Delta\text{TO}_i \cdot r_{i,t-12,t-2}] + \epsilon_{i,t}\,, \end{aligned} \tag{2}$$

within PIN portfolios. With the predictions of Wang (1994) pertaining to increases in turnover, high turnover is determined on a firm-specific basis. The ΔTO variable is defined as a firm's turnover in month $t-1$ relative to its turnover during the intermediate past return horizon from month $t-12$ to month $t-2$. Double-sorted portfolios in the next section condition on the level of turnover, as in Lee and Swaminathan (2000)'s momentum study.

As reported in Table III, the β_6 coefficients for the interaction variable $\Delta\text{TO} \cdot r_{t-12,t-2}$ across the PIN portfolios are consistent with the predictions of Wang (1994). In particular, the low PIN portfolio has a negative coefficient, indicating return reversals, while the high PIN portfolio has a positive coefficient. More importantly, the difference between the β_6 coefficients of the high PIN and low PIN portfolios, 0.0129, is significant (t-statistic of 2.24). Indeed, only β_3 and β_6 are significantly different in the low PIN portfolio versus the high PIN portfolio. The 0.0308 disparity (t-statistic of 3.14) between the β_3 coefficients indicates that short-term return reversals are less pronounced in high PIN stocks. Consequently, stocks with more informed trading experience weaker short-term return reversals.

Although informed investors are inactive when they do not posses private information or when their investment opportunities have not changed, these inactive periods can be infrequent. Consequently, provided informed investors trade regularly, the influence of informed trading on return continuation is expected to dominate turnover's influence. For example, when asymmetric information is time-varying, constant turnover does not reduce the uncertainty surrounding informed trading from the perspective of uninformed investors. This uncertainty is of primary importance when distinguishing between return continuation and return reversals in Wang (1994)'s learning model.

B. Order Flow Imbalances and Residual Informed Trading

To alleviate concerns that cumulative order flow imbalances are responsible for return continuation and determining the PIN estimates, we investigate order flow imbalances during the holding period. These order flow imbalances are negatively correlated with PIN, while the correlation between PIN and the absolute value of order flow imbalances equals 0.237.[9] Besides being positively correlated with PIN, the absolute value accounts for the impact of large negative imbalances on the returns from short-selling past losers. These two properties imply that the absolute value of order flow imbalances is more relevant to our momentum study.

The correlation between PIN and the volatility of daily order flow imbalances equals 0.618. This high correlation is intuitive since an alternating sequence of large positive and large negative daily order flow imbalances result in a high PIN, while the cumulative order flow imbalance of this sequence may be near zero. Conversely, a series of small order flow imbalances with the same sign creates a large cumulative imbalance but a low PIN. Hence, PIN and the volatility of order flow imbalances both depend on the frequency of large daily imbalances (irrespective of their sign) more than cumulative imbalances.

We construct residual probabilities of information trading (RPIN) each month that simultaneously account for multiple uncertainty and liquidity characteristics as well as order flow imbalances. RPIN estimates are obtained each month from the following cross-sectional regression

$$\begin{aligned} \mathrm{PIN}_{i,t} \;\; = \;\; & \gamma_0 + \gamma_1 \, \mathrm{Disp}_{i,t} + \gamma_2 \, \mathrm{Cov}_{i,t} + \gamma_3 \, R^2_{i,t} + \gamma_4 \, \ln\left(\mathrm{Size}\right)_{i,t} \\ & + \gamma_5 \, \mathrm{Lambda}_{i,t} + \gamma_6 \, \mathrm{ES}_{i,t} + \gamma_7 \, \left|\mathrm{OIB}\right|_{i,t} + \nu_{i,t} \, . \end{aligned} \tag{3}$$

The Cov and ES variables denote analyst coverage and the effective spread respectively, while |OIB| refers to the absolute value of order flow imbalances.[10] The combination of intercepts and

[9] Annual order flow imbalances that coincide with the estimation of PIN are also examined. However, annual imbalances are virtually independent of momentum returns and have a far weaker correlation with PIN.

[10] PIN, lambda, and the effective spread are constant within each calendar year, while the remaining variables are computed monthly. Persistence in forecast dispersion, analyst coverage, return R^2, and size leads to similar

residuals in equation (3) represent firm-specific residual probabilities of informed trading, with RPIN_i defined as $\gamma_0 + \nu_i$.

Three different nested specifications of equation (3) are estimated. The first specification is limited to uncertainty (γ_5, γ_6, and γ_7 are zero), and produces RPIN1 residuals. The second specification yields RPIN2 residuals by examining the influence of uncertainty and liquidity on informed trading (γ_7 is zero), while RPIN3 residuals account for uncertainty, liquidity, and the absolute value of order flow imbalances.

The three sets of RPIN estimates from equation (3) are incorporated into an interaction variable $\text{RPIN}_t \cdot r_{t-12,t-2}$ that parallels its earlier counterpart defined by PIN_{t^*}. We then estimate a special case of equation (1)

$$\begin{aligned} r_{i,t} &= \beta_0 + \beta_1 \ln(\text{Size})_{i,t-1} + \beta_2 \text{BM}_{i,t-1} + \beta_3 \, r_{i,t-1,t} + \beta_4 \, r_{i,t-12,t-2} + \beta_5 \, r_{i,t-60,t-13} \\ &\quad + \beta_6 \, [\text{RPIN}_{i,t} \cdot r_{i,t-12,t-2}] + \epsilon_{i,t} \,, \end{aligned} \tag{4}$$

since cross-sectional differences in uncertainty are incorporated into all three RPIN estimates, while cross-sectional differences in liquidity are incorporated in RPIN2 and RPIN3.

Table IV reports significant β_6 coefficients for each of the three RPIN specifications. A slight decline in β_6 from 0.2010 to 0.1658 accompanies the addition of liquidity proxies and the absolute value of order flow imbalances to equation (3). Thus, the influence of informed trading on return continuation is not attributable to uncertainty, liquidity, nor order flow imbalances.

Adding the interaction variable $|\text{OIB}|_t \cdot r_{t-12,t-2}$ to equation (1) does not reduce the magnitude nor the significance of the $\text{PIN}_{t^*} \cdot r_{t-12,t-2}$ interaction variable. While significantly positive, the coefficient for the $|\text{OIB}|_t \cdot r_{t-12,t-2}$ interaction variable is difficult to interpret. A combination of autocorrelation in monthly order flow imbalances in conjunction with the high correlation between contemporaneous order flow imbalances and returns can explain its significance.[11]

C. Existing Empirical Evidence

Jackson and Johnson (2006) report that momentum is concentrated in firms experiencing corporate events such as mergers and acquisitions that alter expected cashflows. These events likely

results when equation (3) is estimated using their averages over every calendar year.

[11] Chordia and Subrahmanyam (2004) document that order flow imbalances over short horizons predict returns, causing positive and then subsequently negative return autocorrelation.

stimulate informed trading. Avramov, Chordia, Jostova, and Philipov (2007) find stronger momentum in stocks with lower credit ratings, while Odders-White and Ready (2005) report that firms with lower credit ratings have more informed trading. When combined, informed trading can explain the stronger return continuation in stocks with lower credit ratings. Intuitively, firms on a credit-watch are likely to be closely monitored by debtholders, customers, suppliers, and other stakeholders willing to trade on their private information.

Hvidkjaer (2006) finds the impact of small trade imbalances on returns is more pronounced for stocks with high turnover. Provided uninformed investors execute small trades and gradually learn about the presence of informed trading, small trade imbalances reflect private information that was previously known by informed investors. Thus, the results in Hvidkjaer (2006) are consistent with uninformed investors becoming informed.

The empirical results in Liang (2006) confirm that stocks with higher PIN measures exhibit stronger momentum across the sixteen strategies in Jegadeesh and Titman (1993). However, there are several theoretical differences between the models of Liang (2006) and Wang (1994) that yield distinct testable implications. In Liang (2006), the motivation underlying trades by informed investors is not uncertain. Instead, as private information is revealed, uninformed investors trade against informed investors rather than imitating their prior trades. This conflict culminates has informed investors becoming contrarian. In addition, Liang (2006) does not examine the interaction between informed trading and turnover.

III Momentum Implications

We form double-sorted portfolios to examine the influence of informed trading on momentum returns. The interaction between turnover and PIN on momentum returns is also investigated, along with controls for uncertainty and liquidity characteristics as well as order flow imbalances.

As in Zhang (2006) and Hou, Peng, and Xiong (2006), a 12-1-1 momentum strategy with a twelve month formation period and a one month holding period is examined with a one month interval inserted between these periods. Similar results are obtained from an alternative 6-1-6 momentum strategy with six month formation and holding periods. The monthly stock returns underlying these momentum strategies are obtained from CRSP. Value-weighted momentum returns are examined for completeness since cross-sectional regressions implicitly equally-weight each firm.

A. Turnover

We begin by double-sorting stocks into portfolios according to their PIN and their turnover during the last month of the formation period. Lee and Swaminathan (2000)'s momentum study also examines the level of turnover. They find that stocks with high turnover have stronger momentum, but interpret turnover as a proxy for investor sentiment.

Table V reports that stocks in the P4-TO4 portfolio with high turnover and high PIN have the strongest momentum amongst all the double-sorted portfolios, 2.41% on average (t-statistic of 3.66). However, as predicted by Wang (1994), high turnover does not imply stronger momentum unless accompanied by high informed trading.[12] Indeed, stocks in the P1-T04 portfolio with high turnover and low PIN exhibit return reversals, albeit insignificant, averaging -0.54% (t-statistic of -1.03). This negative return is the lowest amongst all the double-sorted portfolios. The weaker evidence of return reversals, in comparison to return continuation, may be attributed to our holding period beginning one month after the formation period. Jegadeesh (1990) documents return reversals in individual stocks within monthly horizons, while Avramov, Chordia, and Goyal (2006) conclude that weekly return reversals are induced by liquidity shocks.

Adjusting the monthly returns of individual stocks for market, book-to-market, and size factors along with the liquidity factor in Pástor and Stambaugh (2003) does not alter our conclusions as risk-adjusted momentum returns continue to increase across the PIN portfolios.[13] Replacing Pástor and Stambaugh (2003)'s liquidity factor with its counterpart in Sadka (2006) yields similar empirical results.

The reverse double-sorts also demonstrate the importance of informed trading. In unreported

[12]Quartiles ensure there are sufficient stocks available to compute momentum returns after sorting stocks according to their PIN, turnover, and past returns. With quartiles for PIN and turnover, the sorting procedure underlying Table V involves computing unadjusted and risk-adjusted returns for 80 portfolios; 4 PIN portfolios times 4 turnover portfolios times 5 past return portfolios. PIN and turnover quintiles would involve 125 portfolios, each containing very few stocks. Quintiles are investigated in Table VI since portfolio returns are only computed for 25 portfolios.

[13]Pástor and Stambaugh (2003) demonstrate that their liquidity factor accounts for a substantial component of momentum over annual horizons. However, over monthly horizons, returns from their liquidity factor are far more variable than momentum returns.

results, after stocks are first sorted into turnover quartiles, those with the highest PIN exhibit the strongest momentum while low PIN stocks exhibit return reversals.

B. Firm Characteristics

We also double-sort stocks into PIN quintiles after accounting for their uncertainty and liquidity characteristics. These double-sorted portfolios are constructed sequentially to ensure each portfolio contains the same number of stocks.[14]

To create size-neutralized portfolios, stocks are first sorted into size quintiles. The five low PIN portfolios are then combined across each of the size quintiles, and summarized as P1. This combination of PIN quintiles, within size portfolios, is then conducted to form the P2 through P5 portfolios. This procedure is also applied to the remaining uncertainty proxies as well as the effective spread, lambda, and order flow imbalances.

After controlling for size, Panel A of Table VI reports that momentum continues to increase with informed trading, from an insignificant 0.28% (t-statistic of 0.78) in the low PIN portfolio to 1.19% (t-statistic of 2.77) in the high PIN portfolio. Furthermore, the relationship between momentum and PIN cannot be attributed to analyst forecast dispersion. Specifically, within the dispersion-neutralized portfolios, momentum increases with informed trading, from an insignificant 0.15% (t-statistic of 0.42) in the P1 portfolio to a highly significant 1.54% (t-statistic of 3.73) in the P5 portfolio. Unreported analyst coverage and return R^2 results are nearly identical. Cross-sectional differences in Kyle (1985)'s lambda also cannot explain the relationship between between momentum and informed trading. For example, within lambda-neutralized portfolios, momentum returns are increasing with PIN, from 0.17% (t-statistic of 0.38) in the P1 portfolio to 1.44% (t-statistic of 2.26) in the P5 portfolio. A similar unreported pattern is observed after controlling for effective spreads.

Panel A of Table VI also demonstrates that momentum returns increase across the PIN portfolios after accounting for the absolute value of order flow imbalances. Indeed, momentum returns of 2.02% in the P5 portfolio are more than double those in the P4 portfolio, and far more significant, while stocks with less informed trading exhibit insignificant momentum.

Reverse double-sorts that first classify stocks into PIN quintiles and then additional firm

[14] An independent sort yields too many large (too few small) stocks with low informed trading.

characteristics are also evaluated. In unreported results, there is no pattern in momentum returns across the size, forecast dispersion, analyst coverage, return R^2, lambda, effective spread, and order flow imbalance portfolios after accounting for informed trading.

To simultaneously account for uncertainty and liquidity characteristics as well as order flow imbalances, residual probabilities of informed trading are examined. After estimating the regression in equation (3), stocks are sorted into RPIN quintiles according to their residuals. Even without accounting for turnover, the results in Panel B of Table VI confirm that momentum returns are monotonically increasing from 0.21% in the low RPIN portfolio to 1.09% in the high RPIN portfolio.

IV Prior PIN

In Wang (1994), uninformed investors are initially uncertain about the motives of informed investors. However, if informed trading is highly predictable, then less uncertainty surrounds informed trading. We investigate PIN estimates from the prior calendar year to assess the economic implications of time-varying asymmetric information in terms of return continuation.[15] This variability is not required to justify a risk premium for informed trading but is crucial for testing the learning motivation in Wang (1994). For emphasis, from the perspective of uninformed investors, uncertainty regarding the motivation of informed investors does not correspond with PIN being either high or low.[16] Instead, a weak relationship between prior PIN estimates and return continuation is consistent with the level of asymmetric information being uncertain.

Prior PIN is denoted PIN_{t^*-1} where $t^* - 1$ refers to the calendar year before the month t holding period. To test the relationship between prior PIN and return continuation, we study the interaction variable $\text{PIN}_{t^*-1} \cdot r_{t-12,t-2}$. Both elements of $\text{PIN}_{t^*-1} \cdot r_{t-12,t-2}$ are constructed before the holding period in month t. With PIN estimated over annual calendar-time horizons, the intermediate past return horizon $r_{t-12,t-2}$ often coincides with the estimation period underlying PIN_{t^*-1} as well as PIN_{t^*}. Nonetheless, overlap in the $r_{t-12,t-2}$ component of these interaction variables is inconsequential to our analysis of informed trading.

[15] We thank Jiang Wang for clarifying the importance of time series variation in the PIN estimates.

[16] If uninformed investors know the true level of informed trading, stock prices adjust rapidly with little return continuation in a high PIN environment, while price impacts are limited in a low PIN environment.

Two cross-sectional regressions are performed. The first replaces the interaction variable in equation (1) with $\text{PIN}_{t^*-1} \cdot r_{t-12,t-2}$. As reported in Panel A of Table VII, the coefficient for $\text{PIN}_{t^*-1} \cdot r_{t-12,t-2}$ equals 0.0026 and is insignificant (t-statistic of 0.12), even without controlling for forecast dispersion and lambda. This finding supports the economic intuition in Wang (1994). Indeed, a strong relationship between prior PIN estimates and return continuation would undermine the need for learning.

The second cross-sectional regression investigates the interaction variable defined by PIN_{t^*-1} and PIN_{t^*} simultaneously. The inclusion of $\text{PIN}_{t^*-1} \cdot r_{t-12,t-2}$ in equation (1) does not eliminate the significance of the original interaction variable defined by PIN_{t^*}. Furthermore, the coefficient of 0.1272 for $\text{PIN}_{t^*} \cdot r_{t-12,t-2}$ differs from the -0.0060 coefficient for $\text{PIN}_{t^*-1} \cdot r_{t-12,t-2}$. The disparity between these interaction variable coefficients further highlights the economic significance of time variation in the PIN estimates.

Double-sorted portfolios are also constructed to investigate the ability of prior PIN estimates to generate stronger momentum returns. In particular, Wang (1994)'s learning model does not imply the existence of more profitable momentum trading strategies. Nonetheless, autocorrelation in the firm-specific PIN estimates averages 0.27. This predictability can undermine the need for learning to reduce uncertainty if higher momentum returns are available from simply conditioning on prior PIN estimates and past returns.

Panel B of Table VII documents that significant momentum returns are limited to stocks in the three highest prior PIN quintiles, while momentum returns in the bottom two prior PIN quintiles are insignificant. This evidence suggests that higher momentum returns are available after conditioning momentum strategies on prior PIN estimates. However, size eliminates the marginal importance of prior PIN to momentum returns.[17] Replacing size with firm characteristics such as analyst forecast dispersion yields similar results. Therefore, although the uncertainty proxies are related to informed trading, momentum investors cannot rely on predictability in firm-specific PIN estimates to earn higher returns. This result supports the economic intuition in Wang (1994) as learning is required to overcome uncertainty regarding asymmetric information.

[17] The size-neutralized portfolios are constructed using the same procedure as those in Panel A of Table VI.

V Discussion and Implications

To our knowledge, we are the first to document the importance of informed trading to short-term return continuation. This relationship has important implications for explaining the existence of momentum and its continued persistence.

A. Rational Interpretation

Our empirical evidence supports the predictions of Wang (1994)'s price discovery model as return continuation is strongest for stocks with a combination of high turnover and high informed trading. Conversely, stocks with high turnover and low informed trading fail to exhibit return continuation. This finding contradicts Lee and Swaminathan (2000)'s interpretation of turnover as a proxy for investor sentiment.

In the absence of informed trading, Lewellen and Shanken (2002) demonstrate that cash-flow uncertainty can generate return predictability as a result of learning. However, our results indicate that asymmetric information is crucial to return continuation. Thus, our findings confirm Hong and Stein (1999)'s insight regarding the importance of investor heterogeneity and asymmetric information to return continuation.

Furthermore, momentum returns have almost zero *net* exposure to informed trading since the past winner and past loser portfolios have nearly identical average PIN estimates.[18] As a consequence, a risk factor for informed trading cannot capture the importance of asymmetric information to momentum returns. Exposure to systematic liquidity also differs from the influence of firm-specific asymmetric information since time series variation in PIN does not necessarily induce systematic liquidity fluctuations. Empirically, the P1 and P5 portfolio have average PIN measures that exhibit little variation over time.

B. Behavioral Interpretation

The informed investor in Daniel, Hirshleifer, and Subrahmanyam (1998) overreacts to private signals due to their overconfidence. The representativeness bias in Barberis, Shleifer, and Vishny

[18]Within the high PIN portfolio, the average PIN of past losers and past winners equal 0.295 and 0.292 respectively. Within the low PIN portfolio, the average PIN of past losers is 0.125, while past winners have an average PIN of 0.120.

(1998) also induces an overreaction. In these behavioral models, long-term return reversals are the consequence of investor overreaction.

Figure 1 plots the long-term value-weighted momentum returns across PIN quintiles.[19] Stocks with higher informed trading experience weaker return reversals after stronger momentum. Thus, Figure 1 suggests that momentum is not caused by investor overreactions. George and Hwang (2004) also report that momentum and reversals occur in different subsets of stocks. We extend their results by demonstrating the role of informed trading in separating these subsets.

By allowing investor psychology to create persistent mispricings, the limits to arbitrage assumption is the cornerstone of behavioral finance. The limits to arbitrage argument in Shleifer and Vishny (1997) is motivated by the presence of noise traders (and agency costs). PIN measures the percentage of trades that are motivated by private information, with noise trading being more prevalent in low PIN stocks. Indeed, a higher percentage of informed trades reduces the percentage of noise trades. Our empirical results document stronger return continuation in high PIN stocks, which contradicts the limits to arbitrage prediction that this anomaly is due to the presence of noise traders. Brav and Heaton (2006) also cast doubt on the standard limits to arbitrage explanation for momentum.

In summary, our results stress the need to consider information-based trading as a source of momentum in future theoretical as well as empirical research.

C. Persistence of Momentum

Our empirical results indicate that informed trading determines momentum returns *before* transaction costs. Informed trading also contributes to our understanding of momentum's persistence since informed trading increases the transaction costs associated with purchasing past winners and selling past losers. By increasing the cost of implementing momentum strategies, informed trading inhibits the ability of arbitrageurs to eliminate momentum.

Determining whether momentum strategies yield abnormal returns *after* transaction costs is beyond the scope of this paper since the appropriate methodology for measuring the price-impact of informed trading is controversial. After estimating a concave price-impact function,

[19] The cumulative momentum returns in Figure 1, which *begin* in month t, are not comparable to the β_5 coefficients from equation (1) that measure the cross-sectional relationship between holding period returns in month t and past returns over the month $t-13$ to month $t-60$ horizon.

Chen, Stanzl, and Watanabe (2002) conclude that only small amounts can be invested in momentum strategies before their abnormal returns are eliminated. Lesmond, Schill, and Zhou (2003) also report that momentum returns are insignificant after accounting for transaction costs. In contrast, Korajczyk and Sadka (2004) employ a linear price-impact function and determine that large positions can be invested in momentum strategies before their abnormal returns disappear.[20]

To our knowledge, the existing literature has not explicitly accounted for asymmetric information when estimating the transaction costs of momentum strategies. However, Keim (2003) emphasizes the importance of investment style to institutional transaction costs. Consistent with momentum's persistence being attributable to informed trading, Keim (2003) reports that momentum strategies have higher transaction costs than value strategies and diversified investment strategies.

VI Conclusions

We document that return continuation is stronger for stocks with higher probabilities of informed trading. Although greater uncertainty coincides with higher informed trading, the relationship between return continuation and informed trading is robust to controlling for uncertainty proxies such as analyst forecast dispersion, analyst coverage, idiosyncratic return volatility, and size. The influence of informed trading on return continuation also cannot be attributed to cross-sectional differences in liquidity and order flow imbalances.

Instead, our results indicate that price discovery is responsible for short-term price momentum. In Wang (1994), uninformed investors gradually learn about the private information possessed by informed investors. Learning causes uninformed investors to update their cashflow expectations and imitate the earlier trades of informed investors. Thus, when turnover arises from informed trading, learning generates return continuation. Conversely, turnover that is not attributable to private information leads to temporary reductions in liquidity that induce subsequent return reversals.

[20]Korajczyk and Sadka (2004) estimate trading costs in-sample over the January 1993 to May 1997 subperiod before estimating these costs out-of-sample by conditioning on nine firm characteristics. This out-of-sample estimation of trading costs does not account for time-variation in informed trading.

As predicted by Wang (1994), stocks with high informed trading and high turnover experience the strongest return continuation, while stocks with low informed trading and high turnover experience return reversals. Furthermore, momentum returns are confined to stocks with high levels of informed trading. Thus, contrary to the underlying motivation for limits to arbitrage, stronger momentum occurs in stocks with greater informed trading that have lower noise trader risk.

Our empirical results stress the importance of informed trading to future theoretical and empirical research on price momentum. One avenue for future research involves a re-evaluation of the transaction costs incurred by momentum strategies after conditioning on firm-specific and time-varying measures of informed trading. Prior research has estimated these transaction costs using firm characteristics such as size that are less important to return continuation than informed trading at the firm level.

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Table I. Characteristics of PIN Portfolios

This table reports the time series averages of firm characteristics across PIN-sorted portfolios and their pairwise correlations. PIN refers to the probability of informed trading. The sample period is January 1989 to December 2001 for lambda and the effective spread, and January 1983 to December 2001 for the remaining characteristics. Each year, firms are sorted into five PIN portfolios and the cross-sectional average of each characteristic is computed within each quintile. The time series averages corresponding to these annual cross-sectional averages are then reported in Panel A. The price-impact measure lambda and the effective spread are estimated from the TAQ database. Size is the market capitalization of a firm in millions of dollars. Turnover represents a firm's monthly turnover ratio divided by the number of its shares outstanding. IVOL denotes idiosyncratic volatility, computed using each firm's weekly returns over the past year. The return R^2 statistic is estimated by regressing a firm's weekly return on the return of the market and its industry over the past year. Analyst dispersion is the standard deviation of analysts' earnings forecasts for the next fiscal year divided by the firm's stock price. Analyst coverage is the number of analysts following a stock. Panel B reports the average pairwise correlations between these firm characteristics. The correlation coefficients are estimated using monthly observations.

Panel A: Characteristics of PIN-sorted portfolios

	PIN	Lambda	Effective Spread	Size	Turnover	IVOL	Return R^2	Analyst Dispersion	Analyst Coverage
P1	0.12	0.76	0.41	6261	0.066	0.045	0.31	0.013	16.6
P2	0.16	1.54	0.61	1485	0.070	0.055	0.24	0.014	10.5
P3	0.20	2.72	0.85	664	0.066	0.063	0.19	0.018	6.9
P4	0.24	4.97	1.09	314	0.055	0.070	0.15	0.035	4.8
P5	0.34	9.45	1.38	151	0.041	0.076	0.12	0.034	3.1

Panel B: Pairwise Pearson Correlations

PIN	1.00	0.28	0.46	-0.30	-0.18	0.28	-0.42	0.07	-0.53
Lambda		1.00	0.63	-0.10	-0.14	0.28	-0.24	0.26	-0.29
Effective Spread			1.00	-0.26	-0.10	0.53	-0.45	0.48	-0.51
Size				1.00	-0.01	-0.17	0.36	-0.04	0.54
Turnover					1.00	0.19	0.12	0.04	0.11
IVOL						1.00	-0.29	0.31	-0.32
Return R^2							1.00	-0.09	0.60
Analyst Dispersion								1.00	-0.06
Analyst Coverage									1.00

Table II. Return Continuation

This table summarizes the estimated coefficients from several nested specifications of the cross-sectional regression in equation (1). The dependent variable in this regression is the unadjusted return of individual stocks in month *t*. The independent variables control for size and book-to-market characteristics, as well as past returns over three non-overlapping horizons with $r_{t-12,t-2}$ denoting an intermediate horizon that corresponds to the formation period of momentum strategies. To analyze the role of informed trading, the cross-sectional regression includes up to three interaction terms between past intermediate returns and PIN, analyst forecast dispersion (Disp), and Kyle (1985)'s lambda. PIN and lambda pertain to the calendar year *t** that contains month *t*. The second row in bold contains *t*-statistics for each of the estimated coefficients.

Model Specification	β_1 ln(Size)	β_2 B/M	β_3 $r_{t-1,t}$	β_4 $r_{t-12,t-2}$	β_5 $r_{t-60,t-13}$	β_6 $PIN_{t^*} \bullet r_{t-12,t-2}$	β_7 $Disp_{t-1} \bullet r_{t-12,t-2}$	β_8 $Lambda_{t^*} \bullet r_{t-12,t-2}$
1	0.0116	0.0025	-0.0250	0.0063	-0.0005			
	1.26	***1.24***	***-3.07***	***2.16***	***-1.26***			
2	0.0152	0.0027	-0.0261	-0.0080	-0.0006	0.0895		
	1.66	***1.33***	***-3.20***	***-1.42***	***-1.35***	***3.60***		
3	0.0112	0.0029	-0.0252	0.0054	-0.0005		0.1363	
	1.22	***1.47***	***-3.05***	***1.80***	***-1.15***		***0.76***	
4	0.0103	0.0027	-0.0249	0.0058	-0.0005			0.0009
	1.12	***1.33***	***-3.04***	***1.89***	***-1.18***			***1.25***
5	0.0149	0.0031	-0.0262	-0.0086	-0.0005	0.0895	0.0985	
	1.63	***1.56***	***-3.18***	***-1.52***	***-1.26***	***3.46***	***0.54***	
6	0.0139	0.0029	-0.0262	-0.0084	-0.0006	0.0936		0.0000
	1.52	***1.39***	***-3.19***	***-1.48***	***-1.29***	***3.58***		***-0.07***
7	0.0137	0.0033	-0.0263	-0.0093	-0.0005	0.0948	0.1252	-0.0002
	1.50	***1.63***	***-3.17***	***-1.65***	***-1.20***	***3.55***	***0.68***	***-0.26***

Table III. PIN, Turnover, and Return Continuation

This table summarizes the relationship between turnover and return continuation across different levels of informed trading. P1 and P4 denote the low PIN portfolio and high PIN portfolio respectively, with the estimated coefficients from equation (2) recorded for each PIN quartile. The dependent variable in this regression is the monthly unadjusted return of individual stocks in month *t*. The independent variables include size and book-to-market characteristics, past returns over three non-overlapping horizons, as well as the interaction term between changes in turnover and past returns over an intermediate horizon from month *t-2* to month *t-12*. The change in turnover (ΔTO) is defined as turnover in month *t-1* minus turnover during this intermediate horizon. Model 1 refers to equation (2) without the ΔTO interaction variable while model 2 includes this interaction variable. The second row in bold contains *t*-statistics for each of the estimated coefficients.

	Model Specification	β_1 ln(Size)	β_2 B/M	β_3 $r_{t-1,t}$	β_4 $r_{t-12,t-2}$	β_5 $r_{t-60,t-13}$	β_6 $\Delta TO \bullet r_{t-12,t-2}$
P1	1	0.0073	0.0052	-0.0403	0.0050	0.0001	
		0.78	***1.82***	***-4.16***	***1.39***	***0.25***	
	2	0.0067	0.0050	-0.0430	0.0043	0.0002	-0.0080
		0.73	***1.77***	***-4.37***	***1.16***	***0.40***	***-1.63***
P2	1	0.0217	0.0059	-0.0414	0.0027	0.0002	
		1.92	***2.51***	***-4.35***	***0.82***	***0.50***	
	2	0.0202	0.0061	-0.0418	0.0043	0.0003	0.0014
		1.80	***2.62***	***-4.42***	***1.26***	***0.60***	***0.38***
P3	1	0.0073	0.0034	-0.0267	0.0022	-0.0009	
		0.66	***1.60***	***-3.23***	***0.80***	***-1.58***	
	2	0.0086	0.0036	-0.0272	0.0034	-0.0008	-0.0006
		0.78	***1.73***	***-3.27***	***1.17***	***-1.42***	***-0.25***
P4	1	0.0114	-0.0002	-0.0115	0.0092	-0.0010	
		1.34	***-0.09***	***-1.57***	***4.36***	***-2.01***	
	2	0.0107	-0.0001	-0.0122	0.0101	-0.0009	0.0049
		1.28	***-0.04***	***-1.65***	***4.66***	***-1.95***	***1.65***
P4-P1	2	0.0040	-0.0051	0.0308	0.0058	-0.0011	0.0129
		0.32	***-1.56***	***3.14***	***1.59***	***-1.68***	***2.24***

Table IV. Residual PIN and Return Continuation

This table reports the estimated coefficients from the cross-sectional regression in equation (4). Residual probabilities of informed trading (RPIN) are first obtained as the intercepts and residuals of the cross-sectional regression in equation (3). These residual probabilities are then combined with past intermediate returns to form interaction variables involving informed trading. The independent variables in equation (4) control for size and book-to-market characteristics, as well as past returns over three non-overlapping horizons. Three sets of residual PIN estimates are examined. RPIN1 accounts for the four uncertainty proxies (forecast dispersion, analyst coverage, return R^2, and size), while RPIN2 also includes Kyle (1985)'s lambda and the effective spread. The RPIN3 estimates supplement these uncertainty and liquidity characteristics with the absolute value of order flow imbalances. The second row in bold contains *t*-statistics for each of the estimated coefficients.

Model Specification	β_1 ln(Size)	β_2 B/M	β_3 $r_{t-1,t}$	β_4 $r_{t-12,t-2}$	β_5 $r_{t-60,t-13}$	β_6 $RPIN1_t \bullet r_{t-12,t-2}$	β_6 $RPIN2_t \bullet r_{t-12,t-2}$	β_6 $RPIN3_t \bullet r_{t-12,t-2}$
1	0.0063	0.0031	-0.0264	0.0056	-0.0006	0.2010		
	0.68	***1.47***	***-3.18***	***1.94***	***-1.27***	***6.59***		
2	0.0074	0.0032	-0.0264	0.0052	-0.0006		0.1970	
	0.79	***1.52***	***-3.18***	***1.81***	***-1.25***		***6.41***	
3	0.0076	0.0032	-0.0262	0.0052	-0.0005			0.1658
	0.81	***1.56***	***-3.16***	***1.81***	***-1.22***			***5.47***

Table V. PIN, Turnover, and Momentum

This table reports on the relation between informed trading, turnover and momentum by constructing double-sorted portfolios. The 12-1-1 momentum strategy is studied. M5 (M1) refers to the portfolio of stocks with the highest (lowest) past returns. A sequential sorting procedure constructs the double-sorted portfolios by first sorting stocks according to PIN, then turnover during the last month of the formation period. These double-sorts examine turnover's effect on momentum returns across different levels of informed trading. Portfolio returns are adjusted using the Fama and French (1993) three factors, along with the liquidity factor of Pástor and Stambaugh (2003). In addition, *t*-statistics are reported for the unadjusted returns and the alpha intercepts from the four-factor model.

							M5-M1 (*t*-statistic)			
		M1	**M2**	**M3**	**M4**	**M5**	**Unadjusted**		**4-Factor Adjusted**	
P1	**TO1**	0.70%	0.92%	1.02%	1.27%	1.42%	**0.72%**	**2.01**	**0.71%**	**1.77**
	TO2	0.91%	1.07%	1.33%	1.18%	1.67%	**0.76%**	**1.94**	**1.00%**	**2.41**
	TO3	1.27%	1.13%	1.26%	1.44%	1.83%	**0.56%**	**1.35**	**0.61%**	**1.34**
	TO4	1.29%	1.13%	0.95%	1.13%	0.76%	**-0.54%**	**-1.03**	**0.13%**	**0.22**
P2	**TO1**	0.25%	0.89%	0.64%	0.88%	1.30%	**1.06%**	**2.70**	**1.33%**	**3.08**
	TO2	0.34%	1.22%	1.38%	1.13%	1.07%	**0.73%**	**1.75**	**1.04%**	**2.26**
	TO3	1.03%	1.25%	1.50%	1.56%	1.72%	**0.69%**	**1.53**	**0.86%**	**1.74**
	TO4	1.18%	1.66%	1.45%	1.79%	1.62%	**0.44%**	**0.72**	**1.33%**	**2.00**
P3	**TO1**	-0.18%	0.67%	0.70%	0.36%	0.61%	**0.79%**	**2.08**	**0.90%**	**2.13**
	TO2	0.07%	0.53%	1.24%	1.26%	1.51%	**1.45%**	**3.55**	**1.31%**	**2.96**
	TO3	0.59%	1.14%	1.13%	1.85%	2.12%	**1.53%**	**3.44**	**1.30%**	**2.67**
	TO4	1.07%	2.00%	2.17%	2.16%	2.70%	**1.64%**	**2.71**	**2.43%**	**3.76**
P4	**TO1**	-0.65%	0.38%	0.52%	0.80%	0.37%	**1.02%**	**2.58**	**1.14%**	**2.59**
	TO2	-0.02%	0.62%	0.69%	0.96%	1.14%	**1.16%**	**3.03**	**0.83%**	**1.97**
	TO3	0.37%	1.34%	1.16%	1.49%	2.36%	**1.99%**	**4.33**	**1.84%**	**3.65**
	TO4	1.73%	2.82%	3.50%	3.22%	4.15%	**2.41%**	**3.66**	**2.62%**	**3.57**

Table VI. PIN, Firm Characteristics, and Momentum

This table reports the importance of PIN to price momentum after controlling for uncertainty, liquidity, and order flow imbalances. The 12-1-1 momentum strategy is studied. The M5 portfolio consists of past winners, while the M1 portfolio contains past losers. A sequential sorting procedure constructs characteristic-neutralized PIN portfolios. In Panel A, stocks are first sorted into size portfolios (S1-small to S5-big) according to their market capitalization. PIN portfolios (PIN1 to PIN5) are then formed within each size portfolio. Size-neutralized PIN portfolios (P1 to P5) are formed by combining these PIN portfolios within each size portfolio (e.g. P1 combines PIN1 across each size portfolio). We then replace size with other proxies for uncertainty, liquidity, and the absolute value of order flow imbalances. Momentum returns are adjusted using the Fama and French (1993) three factors, along with the liquidity factor of Pástor and Stambaugh (2003). In addition, *t*-statistics are reported for the unadjusted returns and alpha intercepts from the four-factor model. Panel B reports the results from the residual PIN approach that regresses PIN on multiple uncertainty and illiquidity characteristics as well as the absolute value of order flow imbalances, as in equation (3). The intercepts and residuals from this regression are referred to as residual probabilities of informed trading (RPIN). After sorting stocks in RPIN quintiles, momentum returns are computed for each portfolio.

Panel A: Sorted on Firm Characteristics, then on PIN

							M5-M1 (*t*-statistic)			
		M1	**M2**	**M3**	**M4**	**M5**	**Unadjusted**		**4-Factor Adjusted**	
	P1	1.24%	1.40%	1.15%	1.31%	1.52%	**0.28%**	**0.78**	**0.24%**	**0.62**
	P2	1.13%	1.06%	1.11%	1.18%	1.47%	**0.33%**	**0.89**	**0.75%**	**1.84**
Size	**P3**	0.90%	0.90%	1.15%	1.40%	1.31%	**0.41%**	**1.06**	**0.77%**	**1.79**
	P4	0.86%	1.26%	1.15%	1.22%	1.55%	**0.69%**	**1.73**	**1.29%**	**2.96**
	P5	0.64%	1.36%	1.58%	1.63%	1.83%	**1.19%**	**2.77**	**1.64%**	**3.49**
	P1	1.36%	1.25%	1.09%	1.33%	1.50%	**0.15%**	**0.42**	**0.28%**	**0.74**
	P2	1.07%	1.12%	1.32%	1.24%	1.26%	**0.19%**	**0.50**	**0.64%**	**1.59**
DISP	**P3**	0.81%	1.08%	1.17%	1.59%	1.63%	**0.83%**	**2.01**	**1.00%**	**2.07**
	P4	0.70%	1.39%	1.41%	1.63%	1.62%	**0.92%**	**2.30**	**1.15%**	**2.60**
	P5	0.63%	1.40%	1.98%	1.87%	2.16%	**1.54%**	**3.73**	**1.63%**	**3.60**
	P1	1.09%	1.20%	1.17%	1.20%	1.26%	**0.17%**	**0.38**	**0.19%**	**0.39**
	P2	0.83%	0.93%	1.01%	0.95%	1.29%	**0.46%**	**1.01**	**0.66%**	**1.35**
Lambda	**P3**	0.83%	1.27%	1.12%	1.30%	1.51%	**0.68%**	**1.27**	**1.04%**	**1.82**
	P4	0.89%	0.80%	1.05%	1.25%	1.79%	**0.90%**	**1.69**	**1.36%**	**2.42**
	P5	0.88%	1.06%	1.67%	1.99%	2.32%	**1.44%**	**2.26**	**1.90%**	**2.75**
	P1	1.12%	1.29%	1.23%	1.42%	1.61%	**0.49%**	**1.25**	**0.52%**	**1.26**
	P2	1.05%	0.93%	0.96%	1.22%	1.37%	**0.32%**	**0.65**	**0.67%**	**1.29**
ABS(OIB)	**P3**	0.41%	0.88%	1.23%	1.10%	1.24%	**0.83%**	**1.64**	**1.25%**	**2.29**
	P4	0.60%	1.00%	1.27%	1.38%	1.50%	**0.91%**	**1.91**	**0.94%**	**1.88**
	P5	0.20%	1.23%	1.59%	1.47%	2.22%	**2.02%**	**4.00**	**1.92%**	**3.59**

Panel B: Sorted on Residual PIN

						M5-M1 (*t*-statistic)			
	M1	**M2**	**M3**	**M4**	**M5**	**Unadjusted**		**4-Factor Adjusted**	
RP1	0.91%	1.01%	1.18%	1.04%	1.12%	**0.21%**	**0.46**	**0.32%**	**0.66**
RP2	0.87%	1.03%	0.99%	1.34%	1.30%	**0.44%**	**1.15**	**0.57%**	**1.43**
RP3	0.97%	1.10%	1.21%	1.22%	1.44%	**0.46%**	**1.05**	**0.66%**	**1.42**
RP4	0.84%	1.33%	1.01%	1.26%	1.74%	**0.90%**	**1.85**	**1.12%**	**2.04**
RP5	0.52%	0.90%	1.30%	1.47%	1.62%	**1.09%**	**1.90**	**1.29%**	**2.22**

Table VII. Prior PIN

A firm's prior PIN estimate denoted PIN_{t^*-1} is defined as its calendar year PIN prior to the PIN_{t^*} estimate in month t. Panel A contains the results from the cross-sectional regression in equation (1) using PIN_{t^*-1}, interacted with past intermediate returns, as well as the original interaction variable defined by PIN_{t^*}. The intermediate past return horizon from month *t-12* to month *t-2* corresponds to the formation period of momentum strategies. The second row in bold contains *t*-statistics for each of the estimated coefficients. Momentum returns from a 12-1-1 momentum strategy are examined in Panel B across prior PIN quintiles. M5 refers to the portfolio of past winners while M1refers to the portfolio of past losers. Momentum returns are also reported for double-sorted portfolios that first sort stocks into size quintiles, then PIN quintiles (as in Table VI).

Panel A: Prior PIN and Momentum

Model Specification	β_1 ln(Size)	β_2 B/M	β_3 $r_{t-1,t}$	β_4 $r_{t-12,t-2}$	β_5 $r_{t-60,t-13}$	β_6 $PIN_{t^*-1} \cdot r_{t-12,t-2}$	β_7 $PIN_{t^*} \cdot r_{t-12,t-2}$
1	0.0098	0.0026	-0.0242	0.0081	-0.0006	0.0026	
	1.09	***1.29***	***-2.98***	***1.43***	***-1.43***	***0.12***	
2	0.0128	0.0028	-0.0257	-0.0026	-0.0006	-0.0600	0.1272
	1.42	***1.38***	***-3.18***	***-0.40***	***-1.48***	***-2.48***	***4.79***

Panel B: Size, Prior PIN, and Momentum

		M1	M2	M3	M4	M5	M5-M1 (*t*-statistic) Unadjusted Returns	
PIN	**P1**	1.19%	1.15%	1.17%	1.26%	1.59%	**0.40%**	**1.08**
	P2	0.94%	0.94%	1.16%	1.33%	1.36%	**0.42%**	**1.13**
	P3	0.52%	0.84%	1.25%	1.55%	1.34%	**0.82%**	**2.04**
	P4	0.66%	1.25%	1.09%	1.21%	1.57%	**0.91%**	**2.37**
	P5	0.27%	1.10%	1.37%	1.17%	1.16%	**0.89%**	**2.18**
Size-Neutralized PIN	**P1**	1.25%	1.10%	1.15%	1.25%	1.50%	**0.25%**	**0.67**
	P2	1.07%	1.27%	1.11%	1.31%	1.66%	**0.59%**	**1.47**
	P3	0.81%	1.08%	1.32%	1.28%	1.57%	**0.76%**	**1.90**
	P4	0.87%	1.00%	1.12%	1.24%	1.46%	**0.60%**	**1.55**
	P5	0.62%	0.90%	1.22%	1.49%	1.16%	**0.54%**	**1.30**

Figure 1. PIN and Long-Term Cumulative Momentum Returns

This figure plots the long-term cumulative value-weighted returns from the 12-1-1 momentum strategy (M5-M1) for each PIN portfolio over the holding period from month t+1 to month t+60. The x-axis represents the post-formation period (in months), while the y-axis displays the cumulative value-weighted return.