Information Asymmetry and the Profitability of Technical Analysis

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Abstract

Do informed investors leave trace in the market? In this paper, we document that the portfolios formed by stocks with high level of probability of informed trading (PIN) earn much higher returns under moving average strategies than the buy-and-hold strategy. The abnormal returns cannot be explained by a Fama-French five-factor model with an additional momentum factor, cannot be explained by transaction costs, and still exist after delaying the trading or controlling for firm sizes, return volatility and income volatility. Portfolios with higher PIN_B, PIN_G, and Adjusted PIN produce similar albeit weaker results.

keywords: Probability of Informed Trading; Technical Analysis; Market Efficiency.

1 Introduction

Technical analysis predicts future market trends by using historical trading data. It is widely used in financial industry by different types of traders (Menkhoff and Taylor, 2007; Menkhoff, 2010; Smith, Wang, Wang and Zychowicz, 2016). Trading-related web sites provide abundant ready-made technical indicators, and commentators and analysts in the media frequently mention technical signals. Such passion for technical analysis, however, receives mixed reactions in the academia. Brock, Lakonishok and LeBaron (1992), LeBaron (1999), Lo, Mamaysky and Wang (2000), Neely (2002), Gehrig and Menkhoff (2006), Park and Irwin (2007), among others, provide strong evidence on the profitability of technical trading in stock returns, stock indices, currencies, and futures. In the opposite camp, Samuelson (1965) and Fama (1970) have long rejected the viability of of technical analysis on theoretical grounds, and recently, Marshall, Cahan and Cahan (2008), Bajgrowicz and

Scaillet (2012), and Shynkevich (2012) do not find empirical evidence that is strong enough to support the validity of technical analysis.

Opponents of technical analysis argue that its success is detrimental to its failure. If certain prices or volume patterns were known to be profitable, then trading on those patterns would destroy themselves. On the other hand, if it were useless to employ technical analysis, then its popularity would be a puzzle. After all, one of the important arguments against technical analysis is that the market is efficient, at least in the weak form. But market efficiency relies on the claim that investors are rational. If investors are rational and the market is efficient, why do they use technical tools?

We speculate that technical analysis works but does not do so universally. Park and Irwin (2007) have listed a few reasons why following technical signals may be profitable, such as an environment with noisy rational expectations, behavioral biases, or herding, and in this paper, we focus on the first reason. Brown and Jennings (1989) show that when information is noisy and security supply is random, prices cannot fully reflect information, and investors may use historical prices to improve their forecasts about future prices. Cespa and Vives (2011) show that rational investors can gain from forming expectations based on historical prices. Although the stock returns are predictable, the investors will face the problem with model uncertainty with incomplete information. Moreover, Zhu and Zhou (2009) shows that a trading strategy using moving average signals will improve expected utilities in asset allocation.

Among the papers discussing technical analysis and information environment, Blume, Easley and O'Hara (1994) offer intriguing arguments. They show that if both means and variances of the signals for prices are random, investors' expected utilities may increase if they use historical prices to estimate the variances. They further argue that if prior information about the security is less precise, and market data contain high-quality information, then technical analysis is effective. In addition, they suggest that some securities, for example, small or less widely followed stocks, are more affected by private instead of public information, and technical analysis is more likely to be successful.

This paper examines Blume et al.'s conjecture that technical analysis works in securities with more private information. We collect the stock return data trading in NYSE and AMEX, and sort them into portfolios with different levels of information asymmetry, proxy by the Probability of Informed Trading (PIN) developed by developed by Easley, O'Hara and their co-authors (1996; 1997; 2002). Following Han, Yang and Zhou (2013), we apply moving average (MA) strategies on the PIN portfolios, and compare their performance with the buy-and-hold strategy. The results largely confirm Blume et al.'s conjecture. The difference in the MA strategy returns between the highest and lowest PIN decile portfolio is 1.772 percent per month. If the buy-and-hold returns are subtracted from the strategy returns, there is still 1.116 percent of return difference. The return difference produces a 1.093 percent alpha in a time-serious regression on the Fama-French five-factor model (2015) with a momentum factor. The positive alpha remains significant when the length of the MA strategy is extended from ten days to twenty and fifty days, and when the portfolio returns are computed by value-weighting. Furthermore, we use alternative information asymmetry measures such as Adjusted PIN (Duarte and Young, 2009) and PIN_B/PIN_G (Brennan et al., 2016), none of them performs as good as PIN, but the direction is the same that portfolios with high levels of informed trading perform better us MA strategies.

While Blume, Easley and O'Hara (1994) suggest the effectiveness of technical analysis depends on the level of private information, they also suggest information uncertainty may help technical analysis. Since Han et al. (2013) have shown that MA strategies work better for portfolios with high return volatility or small firm sizes, it is interesting to know whether the excellent performance of the MA strategies of high-PIN portfolios is due to the correlation between PIN and return volatility or firm size. To answer this question, we sort the stocks into 25 portfolios in a two-dimensional way: it is

PIN or other information measure in one dimension, and firm size, volatility, or variables related to analyst following in the other dimension. We perform MA strategies on these portfolios, compare the strategy returns with buy-and-hold returns, and obtain time-series regression alphas for the return differences. Within these portfolios, MA strategies of the small-firm portfolios sometimes perform less well than the large-firm portfolios, but high-PIN portfolios always out-perform low-PIN portfolios. MA strategies of high-return-volatility portfolios do not necessarily out-perform low-volatility portfolios, but high-PIN portfolios always out-perform low-PIN portfolios. When we replace return volatility with income volatility, measured by the standard deviation of operating incomes, the results are similar. The only variable that can render the return differences between MA and buy-and-hold returns of high-PIN portfolios insignificant is analyst forecast dispersion, but their six-factor alphas are still positively significant.

We do further robustness check. In addition to the traditional break-even-transaction costs, we have delayed the MA trading overnight, which we are not aware to appear in the literature before. Traditional investigations of technical analysis rely on daily data to construct trading signals and to examine the performance of trading strategies. As a result, the closing price used to compute strategy return has also been used to construct trading signals. While it is sometimes possible to implement strategies as such, orders might not be executed if investors submitted limit orders. Even worse, if investors submit market orders, then trading signals might not be realized after trades had been executed. To allow the implementation of trading strategies more realistic, we re-compute the strategy returns by the next-day opening prices when there are trading signals in the previous days. Although such an delay inevitably reduces the profitability of trading strategies, high-PIN (and other information measures) portfolios still perform better under the MA rule than an buy-and-hold strategy. We therefore believe that technical trading rules, at least the MA strategy, work better for the security with high level of information asymmetry.

The remainder of the article is organized as follows. Section 2 briefly describes the data and the information measures used in this paper. Section 3 examines the performance of the MA stragety. Section4 provides robustness check and Section 5 the paper.

2 Data and Methodology

2.1 Information Measures

The key information asymmetry measure used in this paper is the Probability of Informed Trading (PIN). Its variations such as Adjusted PIN developed by Duarte and Young (2009) and PIN_B/PIN_G by Brennan, Huh and Subrahmanyam (2016) are also examined. Suppose that at the beginning of the day, a private information event for a security may take place with probability a, and no event occurs with probability $1 - a$. The event is bad news for the security with probability d and good news with probability $1 - d$. If there is bad news, informed traders may enter the market to sell the securities, and they may buy the security if there is bad news. In either case, the number of their trades made by informed traders follows a Poisson distribution with a rate of u. Furthermore, uninformed trades take places in the market, which follow Poisson distributions with parameters of ϵ_b for purchases and ϵ_s for sales, respectively. The three scenarios in the model as described in Panel A of Figure 1, and the likelihood function can be written as a mixture of bi-variate Poisson distributions

$$L(\Theta \mid B_t, S_t) = \prod_{t=1}^{T} l(\Theta \mid B_t, S_t), \tag{1}$$

where

$$\begin{aligned} l(\Theta \mid B_t, S_t) &= (1-a)e^{-\epsilon_b}\frac{\epsilon_b^{B_t}}{B_t!}e^{-\epsilon_s}\frac{\epsilon_s^{S_t}}{S_t!} + ade^{-\epsilon_b}\frac{\epsilon_b^{B_t}}{B_t!}e^{-(u+\epsilon_s)}\frac{(u+\epsilon_s)^{S_t}}{S_t!} \\ &\quad + a(1-d)e^{-(u+\epsilon_b)}\frac{(u+\epsilon_b)^{B_t}}{B_t!}e^{-\epsilon_s}\frac{\epsilon_s^{S_t}}{S_t!}. \end{aligned} \tag{2}$$

The set of parameters $\Theta = (a, d, \phi) = (a, d, \epsilon_b, \epsilon_s, u)$ is to be estimated for the model using the order flow information B_t and S_t, which are the number of buy and sell trades at day t, respectively. The probability of informed trading is defined as the rate of informed trades divided by the rate of total trades in the market

$$\text{PIN} = \frac{au}{au + \epsilon_b + \epsilon_s}. \tag{3}$$

Brennan et al. (2016) further decompose (3) into the PIN's coming from bad news and good news, which are, respectively,

$$\text{PIN\_B} = \frac{adu}{au + \epsilon_b + \epsilon_s} \text{ and } \text{PIN\_G} = \frac{a(1-d)u}{au + \epsilon_b + \epsilon_s}. \tag{4}$$

Duarte and Young (2009) extend the PIN model to a more general model by assuming that unexpected symmetric order flows may arrive at the market with probability l, and the arrival rates for buy and sell trades are u_b and u_s, respectively.[1] As a result, the model essentially expands the three scenarios in the PIN model into six, which are plotted in Panel B of Figure 1. The likelihood function of the adjusted PIN model is written as

$$L^a(\Theta^a \mid B_t, S_t) = \prod_{t=1}^{T} l^a(\Theta^a \mid B_t, S_t), \tag{5}$$

and

$$\begin{aligned}
l^a \;=\; & (1-a)(1-l)e^{-\epsilon_b}\frac{\epsilon_b^{B_t}}{B_t!}e^{-\epsilon_s}\frac{\epsilon_s^{S_t}}{S_t!} \\
& +(1-a)le^{-(\epsilon_b+\Delta_b)}\frac{(\epsilon_b+\Delta_b)^{B_t}}{B_t!}e^{-(\epsilon_s+\Delta_s)}\frac{(\epsilon_s+\Delta_s)^{S_t}}{S_t!} \\
& +a(1-l)de^{-\epsilon_b}\frac{\epsilon_b^{B_t}}{B_t!}e^{-(u_s+\epsilon_s)}\frac{(u_s+\epsilon_s)^{S_t}}{S_t!} \\
& +alde^{-(\epsilon_b+\Delta_b)}\frac{(\epsilon_b+\Delta_b)^{B_t}}{B_t!}e^{-(u_s+\epsilon_s+\Delta_s)}\frac{(u_s+\epsilon_s+\Delta_s)^{S_t}}{S_t!} \\
& +a(1-l)(1-d)e^{-(u_b+\epsilon_b)}\frac{(u_b+\epsilon_b)^{B_t}}{B_t!}e^{-\epsilon_s}\frac{\epsilon_s^{S_t}}{S_t!} \\
& +al(1-d)e^{-(u_b+\epsilon_b+\Delta_b)}\frac{(u_b+\epsilon_b+\Delta_b)^{B_t}}{B_t!}e^{-(\epsilon_s+\Delta_s)}\frac{(\epsilon_s+\Delta_s)^{S_t}}{S_t!},
\end{aligned} \tag{6}$$

[1]This is Duarte and Young's Model 4, which they claim to be the best model among those tested in their paper.

where $\Theta^a = (a, d, l, \phi^a) = (a, d, l, \epsilon_b, u_b, \Delta_b, \epsilon_s, u_s, \Delta_s)$ is the set of parameters to be estimated for the model. Furthermore, The Adjusted Probability of Informed Trading (AdjPIN) is defined as the ratio of the expected informed order to the total expected order flow

$$AdjPIN = \frac{a((1-d)u_b + du_s)}{a((1-d)u_b + du_s) + l(\Delta_b + \Delta_s) + \epsilon_b + \epsilon_s}. \tag{7}$$

Intraday order-flow data are required to estimate these information measures. We collect the data from ISSM between 1983 and 1992, and from TAQ between 1993 and 2016, use the Lee and Ready's (1991) algorithm to identify buy and sell trades, and sum up daily numbers of trades as B_t and S_t in the above models. Only NYSE and AMEX listed stocks are used in the sample, following Brennan et al. (2016). The Lin and Ke (2011) factorization is used to estimate the PIN models.

2.2 Trading Strategies

Daily stock return and price data are collected from CRSP with share code 10 or 11. To include in the PIN portfolios in year n, a security must have traded at least 30 days in year $n-1$ in order to obtain reliable estimates for the PIN, and it must have traded at the year-end trading day in order to obtain market capitalization data. The stocks are then sorted in to decile portfolios according to their PIN values. The portfolios are assumed to formed at the end of year $n-1$ and held for a year. Because the ISSM data begins in 1983, the trading strategies start in 1984.

We follow Han, Yang and Zhou (2013) to examine the moving average trading strategies. Zhu and Zhou (2009) have shown that MA strategies can help investors to predict and thus can add value to asset allocation, and Zhou and Zhu (2013) provide a direct link of the MAs to future stock returns, which suggest that the MA strategy is likely to be successful.

Denote $P_{j,t}$ the closing price of the equally-weighted portfolio j at date t.

Its moving average price with lag L is defined as

$$A_{j,t,L} = \sum_{l=0}^{L-1} P_{j,t-l}/L. \tag{8}$$

our trading strategy is simply to hold the PIN portfolios if their prices are above the corresponding MA prices, and to hold risk-free assets otherwise. Therefore, the strategy will earn the portfolio returns during continuous up-trend and risk-free rate on the down-trend:

$$\tilde{R}_{j,t,L} = \begin{cases} Rj,t, & \text{if } P_{j,t-1} > A_{j,t-1,L}; \\ r_{f,t}, & \text{otherwise,} \end{cases}, \tag{9}$$

where Rj,t is the daily return of the portfolio j at date t, $r_{f,t}$ is the risk-free rate at t, and $\tilde{R}_{j,t,L}$ is the daily return for the strategy.

3 Profitability of Technical Analysis

3.1 Baseline

Table 1 reports the summary statistics of the MA(10) strategy. We consider $L = 10, 20, 50$ in this paper. Daily portfolio returns, Rj,t, and daily MA(L) returns, $\tilde{R}_{j,t,L}$, are aggregated to be monthly returns Rj,m and $\tilde{R}_{j,m,L}$, respectively. The decile one portfolio earns an average monthly buy-and-hold return of 1.389% while it earns a slightly lower 1.344% using the MA strategy. Both returns increase with PIN, the highest buy-and-hold return takes place in the tenth decile portfolio, and the highest MA return is in the ninth. However, the increase in returns in MA strategy is large. Taking the difference of returns in the highest and lowest decile, the average buy-and-hold return is 0.656%, which is smaller than 1.772% for the MA strategy. Furthermore, the return volatility of this strategy, defined as the standard deviation of the monthly return, is much smaller than that of the buy-and-hold portfolio, the MA strategy generates higher Sharpe ratios in all portfolios. The difference returns are the returns of PIN decile portfolios subtracted from the returns of its corresponding MA(10) strategies:

$$R^d_{j,m,L} = \tilde{R}_{j,m,L} - Rj, m. \tag{10}$$

This return is also increasing in PIN, which indicates that the MA strategy performs better with high PIN stocks. Moreover, the standard deviations of these returns are smaller than those of buy-and-hold returns and MA returns. The last column reports the successful rate of this strategy, which is defined as fraction of the months that the return differences are positive over the sample period. The ratio is also increasing in PIN and is larger than 60% in the last two portfolios, implying that the better performance of the MA strategy is stable.

3.2 alpha

The monthly returns of the difference returns, $R^d_{j,m,L}$, are regressed on an asset price model with five factors in Fama and French (2015) plus a momentum factor:

$$R^d_{j,m,L} = \begin{array}{l} \alpha_j + \beta_{j,b}(R_{M,m} - R_{F,m}) + \beta_{j,s}SMB_m + \beta_{j,h}HML_m + \beta_{j,r}RMW_m \\ +\beta_{j,c}CMA_m + \beta_{j,u}UMD_M + \epsilon_m, \end{array} \tag{11}$$

where the returns from the market factor, $(R_{M,m} - R_{F,m})$, the small-minus-big factor, SMB_m, the high-minus-low factor, HML_m, the robust-minus-weak factor, RMW_m, the conservative-minus-aggressive factor, CMA_m, and the momentum factor, UMD_M, are all retrieved from Kenneth French's web site.[2]. The estimated coefficients of the model are reported in Table 2. All the difference portfolios earns positive alphas, high PIN portfolios tend to earn large alphas, and the highest alpha takes place in the ninth decile. Furthermore, the alphas are all larger than the average of the difference portfolio returns shown in Table 1. The reason for the large alphas is that the portfolios do not only have negative market beta $\beta_{j,b}$, but the factor loadings

[2]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

of HML_m and RMW_m, are also all negative. The loadings of SMB_m for the portfolios with high level of PIN are also negative. This result is similar to Han et al. (2013), where they find the three-factor alphas of their volatility decile portfolios are larger than their returns themselves. In fact, the MA strategy in Equation (9) holds PIN portfolios only when their returns are higher than average past returns, so it naturally has less exposure to the factors.

3.3 length and value-weighted

This section further explores different ways to implement the MA strategy. The length of day lag L is extended from ten to twenty and fifty days, and the PIN portfolio is constructed using both equally- and value-weighted average methods. Table 3 reports the alphas estimated from the six-factor model in (11). The first column reports the MA(10) results from equally-weighted portfolios, which just copies the original estimated alphas from the first column of Table 2. The second and the third columns are respectively the alphas of difference portfolios for MA(20) and MA(50) strategies. All of the alphas are positive, alphas from the high-PIN portfolios tend to be larger than the low-PIN ones, and high-minus-low portfolio still earns significantly positive alphas. However, except for the first portfolio, alphas from longer lags are generally shrinking, which suggests that cautious strategies may miss profitable opportunities.

The next three columns report the alphas from different lag strategies using value-weighted portfolios. The alphas have been reduced further and they turn to negative in the first portfolio. The other patterns are similar to the results from equally-weighted portfolios: MA(50) tends to yield smallest alphas, high-PIN portfolios tend to yield larger alphas, and difference returns in high-minus-low portfolio generate positive alphas that are even larger than those in equally-weighted portfolios.

Given the obvious difference between the results of equally- and value-weighted portfolios, it is likely that the effectiveness of the MA strategies may be different among large and small firms. In fact, Han et al. (2013) have been reported that small firms yield higher MA returns, and similar to Aslan et al. (2011), the average cross-sectional correlation coefficient between PIN and firm size is -0.534. It is interesting to know whether the abnormal returns of PIN portfolios using MA strategies purely coming from its relationship with firm size, and we will return to this issue in Section 4.3.

3.4 Alternative Measures

Table 4 reports the difference portfolio returns, $R^d_{j,m,L}$, and their six factor alphas for alternative information measures, namely, PIN_B, PIN_G, and Adjusted PIN. Equally-weighted portfolios applying the MA(10) strategy are constructed. Again, portfolios with higher values of PIN_B, PIN_G, and Adjusted PIN tend to have higher difference returns and alphas. On the other hand, the spread of returns and alphas, measured by the high-minus-low portfolios, are all smaller than those in PIN portfolios, and the reduction is especially apparent in the PIN_B and Adjusted PIN portfolios.

4 Robustness Checks

4.1 Next-Day Trading

When it comes to detecting technical signals and implementing strategies, academic studies often rely on daily data, which consist of closing trade prices or the averages of closing bid and ask prices. Moreover, the same closing prices are used to detecting signals and implementing strategies. For example, in our strategy, the closing price for date t, $P_{j,t}$, is used to compute the signal $A_{j,t,L}$ in Equation (8) as well as implementing the trading strategy in (9). It is difficult to be done, although not entirely impossible. The problem might happen when it was too close to tell whether the trading condition would be met. If an investor submitted a limit order, then it would be possible that the order might not be executed while the condition was met. If an investor submitted a market order, then it would be possible that the order might be executed while the condition was not met.

In this section, we modify the trading strategy by implementing it at the opening of the next trading day, thus avoiding the dilemma of submitting limit or market orders when the trading signal is not certain. If there is a buy signal at date $t-1$, then we buy the securities at the opening of date t. If there is a sell signal, then we sell at the next opening. Closing prices are used to construct trading signals as before. Define $P^o_{j,t}$ as the opening price at t, and $P_{j,t}$ remains to be the closing price, then further define open-to-close, close-to-open, and close-to-close returns for Portfolio j as, respectively,

$$\begin{aligned}
R^{oc}_{j,t} &= (P_{j,t} - P^o_{j,t})/p^o_{j,t}, \\
R^{co}_{j,t} &= (P^o_{j,t} - P_{j,t-1})/p_{j,t-1}, \\
Rj,t &= (P_{j,t} - P_{j,t-1})/p_{j,t-1}.
\end{aligned}$$

Note that the definitions above can be adjusted for cash dividends or stock splits. Now the return at time t depends on both the trading signal at $t-1$ and the portfolio holding at that day. Suppose risk-free assets are held at $t-1$, then the next-day return is $r_{f,t}$ if the investor continues holding risk-free assets, or it is $R^{oc}_{j,t}$ if the trading signal suggests the investor to switch to hold a PIN portfolio. Now suppose the investors holds a PIN portfolio at $t-1$, then the next-day return is Rj,t if she keeps holding this portfolio, or it is $(1+R^{co})(1+r_{f,t})-1$ if she sells the portfolio to buy risk-free assets at day t. Therefore, the MA return in (9) can be re-written as

$$\tilde{R}_{j,t,L} = \begin{cases} Rj,t, & \text{if the } j\text{-th portfolio are held at t-1 and } P_{j,t-1} > A_{j,t-1,L}; \\ (1+R^{co})(1+r_{f,t})-1 & \text{if the } j\text{-th portfolio are held at t-1 and } P_{j,t-1} \leq A_{j,t-1,L}; \\ R^{oc}_{j,t} & \text{if risk-free assets are held at} t-1 \text{ and } P_{j,t-1} > A_{j,t-1,L}; \\ r_{f,t} & \text{if risk-free assets are held att-1 and } P_{j,t-1} \leq A_{j,t-1,L}; \end{cases} \tag{12}$$

The opening prices from TAQ and ISSM are required to compute (12). We use opening trade prices whenever they are available. If not, then we use the average of opening bid and ask prices. If they are not available either, then we use the closing price $P_{j,t}$ to replace $P^o_{j,t}$.

Table 5 reports the return difference, $R^d_{j,t,L}$, and its six-factor alpha for four information measures. Panel A reports the results from the MA(10) strategy. Delaying trades to the next opening severely erodes profits. Most of the returns and alphas fall by a third, and positive return difference take places only in the portfolios with high level of information trading. On the other hand, the high-minus-low portfolios are not much affected by the change in strategy, the changes in returns or alpha are much smaller, and sometimes the changes are positive. This is because the falls in the returns and alphas in the first decile portfolios are often quite severe.

Panel B of Table 5 reports the results from the MA(50) strategy. Now only the Decile 9 or 10 portfolios of PIN and PIN_G, and the difference returns and alphas of high-minus-low portfolios are further reduced. In fact, the alphas from PIN_B and Adjusted PIN in those portfolios become insignificant.

4.2 Trading and Costs

Table 6 presents the average yearly holding days, average number of yearly trading, and break-even-transaction costs, which are labeled, respectively, "Holding", "Trading", and "BETC" in the tables, for MA strategies using portfolios sorted by four information asymmetry measures. The numbers of holding days for the MA (10) strategy are between 220 and 240, and those for MA (50) are between 240 and 260. The number of trading times for the MA (10) strategy are between 30 and 40, and those for MA (50) are between 9 and 16. Because the change in fifty-day moving average is relatively small, trading is less frequently triggered, and the days holding those portfolios under this strategy are more than under the MA(10) strategy. Within the same strategy, the differences in holding days and trading times among all sorts of information-measure portfolios are small. However, there are less trading for portfolios with high level of information asymmetry. As a result, the break-even transaction costs, defined as the annual excess return of MA(L) strategy, $\tilde{R}_{j,n,L} - r_{f,n}$, divided by the trading times, are large when information asymmetry is severe. They can be over four percent under the MA(50) strategy.

4.3 Firm Size

Han et al. (2013) show that the moving-average strategy works in both size and volatility decile portfolios. The smaller the size or the larger the volatility, the higher MA strategy return. Since the previous studies such as Aslan et al. (2011) show that PIN is negatively correlated with firm sizes and positively correlated with return volatility, it is of interest to see profitability of the MA strategies for the information-measure portfolios, after controlling for other factors.

The cross-sectional correlation coefficients between the firm size and the information measures range from -0.268 for PIN_B to -0.534 for PIN, which is less than -0.64 as reported by Aslan et al. (2011). To control for the potential effect of the firm size, we use two-dimensional sort to form 25 size-information portfolios using the $n-1$ year(-end) data and applied MA strategies to the return in (9) in year n, and the results are reported in Table 7.

Panel A of the table shows the difference returns, $R^d_{j,m,L}$, of MA(10) strategy for PIN-size portfolios and their six-factor alpha. The columns control for sizes and the rows control for PIN. If small-size portfolios had higher MA returns, we would see decreasing $R^d_{j,m,L}$ and α_j from left to right. No such pattern exists. However, the difference returns from high-PIN rows are often higher than the returns from low-PIN rows, and the alphas from the highest-PIN portfolios are all positively significant, which indicates that after controlling firm size, the MA strategy still works in high-PIN portfolios. Turning to Panel B, which shows the results from the MA(50) strategy, the returns become small in general, and the only significant difference return takes place in the group with smallest size and highest PIN. On the other hand, quite a large number of portfolios in the fourth or fifth PIN quintile have large α_j, and the portfolios from the first or second size quintiles do not necessary have large α_j. It suggest that MA strategies work better for high-PIN securities than small-size stocks.

Panel C, D, and E respectively report the difference MA(10) returns and their alpha for the portfolios sorted by firm sizes and PIN_B, PIN_C, and Adjusted PIN. Similar to the PIN results in the previous two panels, positive $R^d_{j,m,L}$ are rare and a lot of α_j remain significantly positive. Size is more useful to explainα_j than PIN_B, because portfolios in size quintiles one and two tend to have larger alphas than those in four or five, whereas high PIN_B portfolios do not have larger alphas. On the other hand, high-PIN_G portfolios are similar to high-PIN portfolios in the sense that they often have large alphas. There is no clear pattern with the Adjusted PIN portfolios.

4.4 Volatility Measures

In this section, we shall examine the usefulness of the MA strategy in portfolios sorted by both information measures and volatility. Table 8 reports the results of the 25 portfolios sorted by information measures and standard deviations of daily returns. The portfolio formation employs the data at year $n-1$ and the MA strategy is performed in year n. Panel A reports the return differences and their alphas for the MA(10) strategy. The columns control for the standard deviations. If the MA strategy performs better for high-volatile stocks, we would expect the return differences are increasing from the left columns to the right. This property holds for all but the first row. On the other hand, if the MA strategy performs better for high-PIN stocks, we would see return differences are larger in the bottom rows than in the top rows, and this is exactly the case. In terms of alphas, the results are similar in that the alphas of high-volatility portfolios are larger than those of low-volatility portfolios, and the alphas of high-PIN portfolios are larger than hose of low-PIN's.

Panel B presents the results for the MA(50) strategy, which are weaker than the MA(10) results in both return differences and alphas. However, the patterns remain that the returns and alphas of high-PIN portfolios are larger than those of low-PIN's, and those of high-volatility portfolios are larger than those of low-volatility ones. Panel C reports the results for the MA(10) strategy using PIN_B/volatility portfolios. With the exception of the poor performance in the high-PIN_B-high-volatility portfolio, similar patterns exist. The results in Panel D are better: the return differences and their alphas of all of the high-PIN_G (high-volatility) are larger than those of their corresponding low-PIN_G (low-volatility) ones. Panel E reports the results for Adjusted PIN/volatility portfolios. Because of the poor performance in the high-AdjPIN-high-volatility portfolio, the patterns are similar to those in Panel C.

Table 9 reports the result of the 25 portfolios sorted by information measures and income volatility (IVO). To compute the income volatility, we first scale quarterly operating income by end-of-quarter total assets. The we subtract last quarter's ratio from this quarter's. Income volatility is then defined as the standard deviation of the differences in the ratio over five years. The portfolios sorted by income volatility between year $n-1$ and $n-5$ and the information measure estimated in year $n-1$ are used to perform MA strategies in year n. Panel A reports the return differences and alphas of the MA(10) strategy for the PIN-IVO portfolios. While the high-PIN portfolios perform better than the low-PIN ones, high-IVO portfolios do not always perform better. Panel B reports the results of the MA(50) strategy, and again, high-PIN portfolios perform well while high-IVO portfolios do not. Panel C shows that high-PIN_B portfolios do not perform better than the low-PIN_B ones, and four out of five high IVO portfolios perform better than the low-IVO portfolios. However, PIN_G portfolios in Panel D do better while high IVO portfolios do not. The results are mixed in Panel E for the Adjusted PIN/IVO portfolios. Overall, PIN and PIN_G portfolios do better in the MA strategies after considering return and income volatilities.

4.5 Analyst Following

We now examine the portfolios sorted by information measures and analysts-related variables. Table 10 examines analyst following, defined as the number of analysts that follow the security in year $n-1$. Together with information measures, 25 portfolios are sorted. Analysts coverage help investors understand the securities, so less coverage may imply less information. Similar to previous tables, Panel A reports the return differences and their alphas of the portfolios. If less analysts following implies more information uncertainty, and if more uncertainty leads to better performance for technical analysis, as Han et al. (2013) predict, then the returns and the alphas are decreasing from the left columns to the right. This is not the case in this panel, where the returns and alphas of the least covered portfolios may be larger or smaller than those in the most covered portfolios. On the other hand, high-PIN portfolios are consistently gaining high returns and alphas than low-PIN portfolios, and Panel B of the MA(50) strategy continues showing this pattern.

Panel C, D, and E presents the results of the MA(10) strategy on the portfolios sorted by analysts coverage and the other three information measures. In Panel C, neither PIN_B nor coverage does well; the highest return differences or alphas sometimes take places in the third column or the third row. Coverage does not do well in Panel D, either. However, the high PIN_G portfolios in the panel, with the exception of high-PIN_G-high-coverage portfolio, perform better than the low PIN_G portfolios. The results of Panel E are similar to those in Panel D in the sense that coverage does not do well and four out of five high adjusted PIN portfolios perform better than their corresponding low adjusted PIN portfolios. To sum up, analysts coverage does not seem to be a good variables that distinguish the good and poor performance of the MA strategy, and of the four information asymmetry measures, PIN seems to be the best when comparing with coverage.

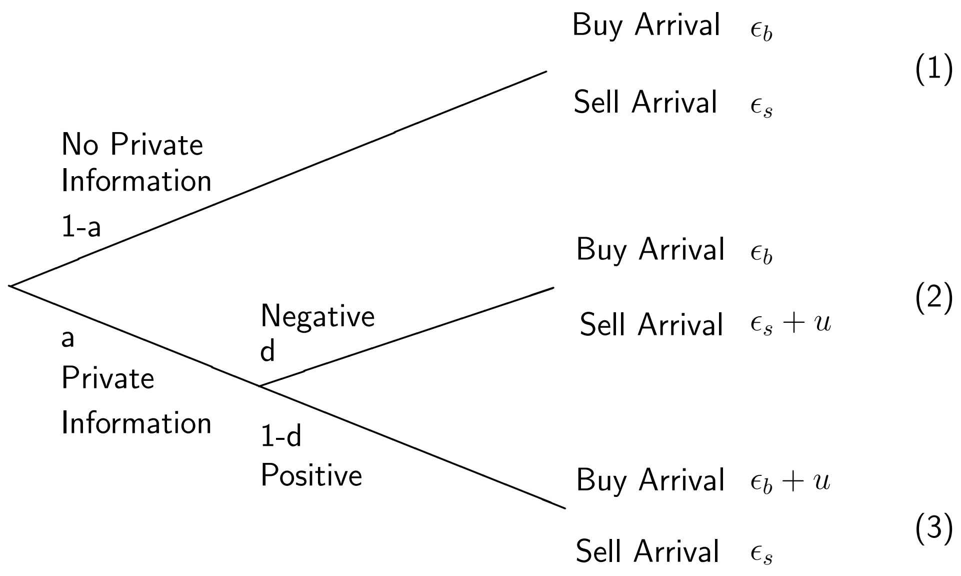
The last exercise examines the performance of the portfolios sorted by information measures and analysts forecasts dispersion. The dispersion is defined as the standard deviation of analysts' year $n-1$ forecasts of earnings per share for year n, divided by the year-end closing price $n-1$. Together with information measures estimated in year $n-1$, 25 portfolios are formed to examine the MA strategy at year n, and the results are reported in Table 11.

Panel A and Panel B of the table respectively report the return differences and their alphas for the MA(10) and MA(50) trading strategies. If dispersion means information uncertainty, then high-dispersion portfolios are expected to exhibit larger return differences and alphas. None of the return difference is significantly positive, but there are large alphas in high-PIN portfolios as well as high-dispersion portfolios except for the portfolio with highest PIN and highest dispersion. In terms of other information measures, PIN_G in Panel D performs best in the sense that all of alphas of the high-PIN_G portfolios are larger than those of the low-PIN_G portfolios, which is not always the case for the high-Adjusted-PIN and especially for the high-PIN_B portfolios.

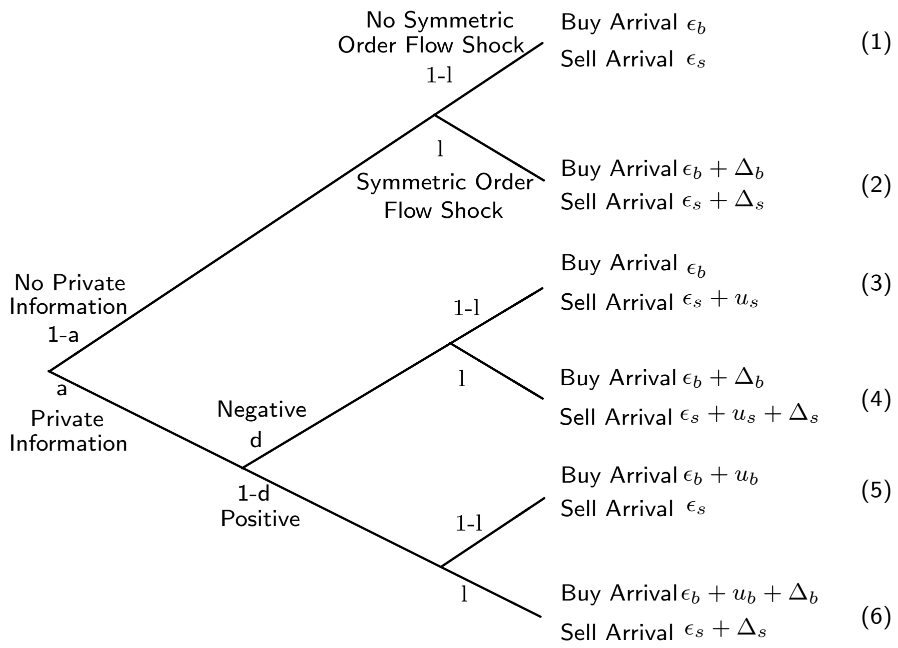
5 Conclusions

This paper documents strong evidence that securities with more private information, proxy by the PIN, obtain higher returns using an MA strategy than a buy-and-hold strategy. This result holds after considering the Fama and French (2015) six factor model together with a momentum factor, varying MA lengths, using equally- or value-weighted portfolio returns, replacing PIN with PIN_B, PIN_G, and Adjusted PIN to form portfolios, and delaying one night for implementing strategies. The return differences remain positive for high-PIN portfolios even when firm sizes, return volatility or income volatility are taken into account. Analyst forecast dispersion is the only variable that may threaten the returns (but not alphas) of the high-PIN portfolios.

This paper only focuses on the moving average strategy, which is one of the most rudimentary tools for technical analysis. Extending the current research to various technical tools may be fruitful. Moreover, this paper is an cross-sectional investigation in the sense that it examines what kinds of securities produce higher returns under technical analysis. It would be interesting to conduct time-series analysis, such as when technical analysis is more fruitful.



Panel A: The PIN Model



Panel B: The Adjusted PIN Model

Figure 1: The PIN and the Adjusted PIN Models

Table 1: Summary Statistics of PIN Portfolios

This table reports average monthly returns, Rj, m , the ten-day moving average returns, $\tilde{R}_{j,m,10}$, and their differences, $R^d_{j,m,10}$, for the portfolios sorted by the level of PIN in the previous years. The mean returns, standard deviations (std), and t-statistics (in parentheses) are reported. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively. For the portfolio and MA strategy returns, the Sharpe ratios are reported. For the return differences, the fractions of the positive differences are reported.

	PIN Portfolios Rj, m			MA(10) $\tilde{R}_{j,m,10}$			Difference $R^d_{j,m,10}$		
Decile	Returns	std	Sharpe	Returns	std	Sharpe	Returns	Std	+ve
Low	1.389***	4.51	0.24	1.344***	3.51	0.30	-0.046	3.05	0.44
	(6.22)			(7.73)			(-0.30)		
2	1.379***	4.85	0.22	1.485***	4.02	0.30	0.107	3.57	0.49
	(5.73)			(7.46)			(0.60)		
3	1.316***	5.20	0.20	1.726***	4.45	0.32	0.409**	4.27	0.53
	(5.10)			(7.82)			(1.93)		
4	1.368***	5.41	0.20	1.862***	4.82	0.32	0.494**	4.44	0.50
	(5.10)			(7.80)			(2.24)		
5	1.401***	5.49	0.20	2.170***	4.86	0.38	0.769***	4.39	0.55
	(5.15)			(9.01)			(3.53)		
6	1.461***	5.65	0.21	2.257***	4.82	0.41	0.796***	4.29	0.53
	(5.22)			(9.45)			(3.74)		
7	1.485***	5.77	0.21	2.625***	4.97	0.47	1.140***	4.23	0.59
	(5.19)			(10.66)			(5.44)		
8	1.672***	5.93	0.23	2.885***	4.45	0.58	1.214***	3.81	0.57
	(5.69)			(13.10)			(6.43)		
9	1.781***	5.91	0.25	3.226***	4.23	0.69	1.445***	3.76	0.63
	(6.08)			(15.40)			(7.76)		
High	2.045***	5.78	0.30	3.115***	4.27	0.66	1.070***	3.44	0.62
	(7.15)			(14.73)			(6.27)		
H-L	0.656***	4.38	0.40	1.772***	3.25	0.87	1.116***	3.21	0.67
	(3.02)			(11.00)			(7.02)		

Table 2: Difference Portfolio with Asset Pricing Models

This table reports the results of time-series regression of the monthly return differences $R^d_{j,m,10}$ on the Fama and French's (2015) five factor models together with a momentum factor in Equation (11):

$$R^d_{j,m,10} = \begin{array}{l} \alpha_j + \beta_{j,b}(R_{M,m} - R_{F,m}) + \beta_{j,s}SMB_m + \beta_{j,h}HML_m + \beta_{j,r}RMW_m \\ +\beta_{j,c}CMA_m + \beta_{j,u}UMD_M + \epsilon_m. \end{array}$$

The coefficients and their t-values (in parentheses) are reported. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively.

Decile	α_j	$\beta_{j,b}$	$\beta_{j,s}$	$\beta_{j,h}$	$\beta_{j,r}$	$\beta_{j,c}$	$\beta_{j,u}$	Adj. R^2
Low	0.449***	-0.469***	0.006	-0.183***	-0.281***	-0.081	0.002	0.3758
	(3.52)	(-14.70)	(0.13)	(-3.05)	(-4.68)	(-0.94)	(0.07)	
2	0.713***	-0.510***	-0.053	-0.261***	-0.383***	-0.130	-0.016	0.3414
	(4.65)	(-13.30)	(-0.97)	(-3.62)	(-5.30)	(-1.25)	(-0.45)	
3	1.173***	-0.606***	-0.055	-0.469***	-0.500***	0.074	-0.096**	0.3719
	(6.54)	(-13.52)	(-0.85)	(-5.56)	(-5.92)	(0.61)	(-2.42)	
4	1.296***	-0.613***	-0.165**	-0.511***	-0.531***	0.078	-0.109***	0.3687
	(6.94)	(-13.11)	(-2.46)	(-5.81)	(-6.03)	(0.61)	(-2.62)	
5	1.490***	-0.597***	-0.195***	-0.460***	-0.463***	0.141	-0.076**	0.3488
	(7.94)	(-12.73)	(-2.90)	(-5.20)	(-5.24)	(1.11)	(-1.83)	
6	1.471***	-0.568***	-0.299***	-0.415***	-0.431***	0.117	-0.050	0.3479
	(8.01)	(-12.36)	(-4.54)	(-4.80)	(-4.98)	(0.94)	(-1.21)	
7	1.802***	-0.595***	-0.245***	-0.396***	-0.342***	0.063	-0.045	0.3675
	(10.12)	(-13.35)	(-3.83)	(-4.72)	(-4.08)	(0.52)	(-1.14)	
8	1.822***	-0.570***	-0.398***	-0.373***	-0.234***	0.122	-0.077**	0.4910
	(12.67)	(-15.85)	(-7.71)	(-5.50)	(-3.45)	(1.25)	(-2.41)	
9	1.954***	-0.539***	-0.334***	-0.188***	-0.193***	-0.015	0.009	0.4271
	(12.98)	(-14.32)	(-6.18)	(-2.65)	(-2.71)	(-0.14)	(0.27)	
High	1.542***	-0.430***	-0.288***	-0.167**	-0.294***	0.000	-0.007	0.3072
	(10.16)	(-11.33)	(-5.28)	(-2.34)	(-4.10)	(0.00)	(-0.22)	
H-L	1.093***	0.038	-0.294***	0.016	-0.013	0.081	-0.010	0.0574
	(6.62)	(0.92)	(-4.96)	(0.20)	(-0.16)	(0.73)	(-0.26)	

Table 3: Variable Length and Equally vs. Value Weighting

The returns of PIN portfolios are computed using either equally-weighted or value-weighted methods. The MA strategies are implemented with time lags of 10, 20, and 50 days to compute the strategy returns. Then the difference between strategy return and portfolio return, $R^d_{j,m,L}$, is regressed on the six-factor model in Equation (11). This table thus reports the alphas and their t-values (in parentheses) of the model. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively.

	Equally-Weighted Portfolios			Value-Weighted Portfolios		
Decile	MA(10)	MA(20)	MA(50)	MA(10)	MA(20)	MA(50)
Low	0.449***	0.528***	0.559***	-0.140	-0.042	-0.048
	(3.52)	(3.98)	(4.02)	(-1.21)	(-0.34)	(-0.37)
2	0.713***	0.767***	0.671***	0.240*	0.164	0.179
	(4.65)	(5.17)	(4.24)	(1.70)	(1.09)	(1.15)
3	1.173***	1.171***	0.944***	0.205	0.293*	0.298*
	(6.54)	(6.62)	(5.08)	(1.23)	(1.68)	(1.77)
4	1.296***	1.256***	1.025***	0.545***	0.501***	0.377**
	(6.94)	(6.88)	(5.34)	(2.78)	(2.74)	(2.01)
5	1.490***	1.431***	1.136***	0.556***	0.411*	0.431**
	(7.94)	(8.31)	(6.20)	(2.71)	(1.93)	(2.12)
6	1.471***	1.497***	1.249***	0.660***	0.513***	0.440**
	(8.01)	(8.67)	(6.64)	(3.20)	(2.71)	(2.22)
7	1.802***	1.784***	1.529***	0.641***	0.589***	0.561***
	(10.12)	(10.91)	(8.94)	(2.85)	(2.78)	(2.77)
8	1.822***	1.810***	1.527***	0.895***	0.803***	0.846***
	(12.67)	(12.92)	(9.88)	(4.14)	(3.71)	(3.81)
9	1.954***	1.857***	1.560***	1.310***	1.275***	0.948***
	(12.98)	(12.37)	(9.75)	(5.95)	(6.13)	(3.86)
High	1.542***	1.505***	1.348***	1.077***	1.308***	1.207***
	(10.16)	(9.87)	(8.56)	(3.46)	(4.32)	(4.01)
H-L	1.093***	0.978***	0.789***	1.217***	1.350***	1.255***
	(6.62)	(5.57)	(4.49)	(3.87)	(4.41)	(4.28)

Table 4: Alternative Measures

This table reports the return differences of the MA(10) strategy, $R^d_{j,m,10}$, and their alphas from the six-factor model in Equation (11), for equally-weighted portfolios sorted by PIN_B, PIN_G, and adjusted PIN. The mean differences, alphas, and their t-values (in parentheses) are reported. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively.

	PIN_B		PIN_G		AdjPIN	
Decile	$R^d_{j,m,10}$	α_j	$R^d_{j,m,10}$	α_j	$R^d_{j,m,10}$	α_j
Low	0.543***	1.220***	0.370*	1.011***	0.456**	1.087***
	(2.82)	(7.50)	(1.91)	(5.96)	(2.41)	(6.70)
2	0.453**	1.101***	0.241	0.840***	0.289	0.869***
	(2.28)	(6.50)	(1.37)	(5.66)	(1.63)	(5.80)
3	0.620***	1.300***	0.275	0.916***	0.291	0.970***
	(3.16)	(8.14)	(1.51)	(5.98)	(1.41)	(5.34)
4	0.558***	1.235***	0.516***	1.182***	0.548***	1.303***
	(2.86)	(7.31)	(2.70)	(7.34)	(2.64)	(7.31)
5	0.545***	1.230***	0.595***	1.256***	0.726***	1.436***
	(2.85)	(7.66)	(3.27)	(8.27)	(3.49)	(8.10)
6	0.763***	1.444***	0.719***	1.348***	0.925***	1.603***
	(4.01)	(9.15)	(3.67)	(8.13)	(4.49)	(9.18)
7	0.840***	1.414***	0.962***	1.604***	0.848***	1.543***
	(4.78)	(9.55)	(4.96)	(10.20)	(4.06)	(9.14)
8	1.135***	1.666***	0.955***	1.582***	1.095***	1.718***
	(6.34)	(10.90)	(5.26)	(10.79)	(5.59)	(11.18)
9	1.008***	1.548***	1.237***	1.865***	1.170***	1.660***
	(5.16)	(9.15)	(6.77)	(12.40)	(6.73)	(12.12)
High	0.944***	1.507***	1.285***	1.823***	0.906***	1.306***
	(5.37)	(9.58)	(6.83)	(11.57)	(5.89)	(9.97)
H-L	0.401**	0.287*	0.915***	0.812***	0.451***	0.220
	(2.48)	(1.71)	(4.93)	(4.45)	(2.67)	(1.32)

Table 5: Trade at the Next Opening

This table reports the results for the MA(10) and MA(50) strategies that are implemented at the open of day t when the signal is observed at the close of $t-1$. The portfolios are sorted by four information measures, namely, PIN, PIN_B, PIN_G, and the adjusted PIN. The return differences $R^d_{j,m,10}$, their alphas for the six-factor model and t-values (in parentheses) are reported. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively.

Panel A: MA(10)

	PIN		PIN_B		PIN_G		AdjPIN	
Decile	$R^d_{j,m,10}$	α_j	$R^d_{j,m,10}$	α_j	$R^d_{j,m,10}$	α_j	$R^d_{j,m,10}$	α_j
Low	-0.360**	0.036	0.052	0.492***	-0.203	0.144	0.026	0.479***
	(-2.45)	(0.30)	(0.29)	(3.64)	(-1.34)	(1.20)	(0.14)	(3.13)
2	-0.162	0.261**	0.029	0.484***	-0.009	0.463***	-0.132	0.311**
	(-1.01)	(2.02)	(0.16)	(3.30)	(-0.04)	(2.70)	(-0.76)	(2.24)
3	0.044	0.554***	0.231	0.715***	-0.098	0.406***	0.052	0.503***
	(0.24)	(3.89)	(1.28)	(5.20)	(-0.58)	(2.94)	(0.28)	(3.31)
4	0.279	0.768***	0.321*	0.794***	0.218	0.694***	-0.020	0.485***
	(1.29)	(4.13)	(1.70)	(5.22)	(1.17)	(4.43)	(-0.11)	(3.36)
5	0.164	0.648***	0.112	0.628***	0.144	0.621***	0.223	0.695***
	(0.86)	(4.39)	(0.64)	(4.80)	(0.85)	(4.57)	(1.17)	(4.58)
6	0.165	0.627***	0.164	0.629***	0.207	0.640***	0.265	0.722***
	(0.87)	(4.21)	(1.00)	(4.99)	(1.18)	(4.72)	(1.37)	(4.76)
7	0.294	0.708***	0.229	0.670***	0.347*	0.822***	0.167	0.600***
	(1.54)	(4.59)	(1.46)	(5.43)	(1.92)	(5.93)	(0.91)	(4.26)
8	0.360**	0.808***	0.302*	0.743***	0.280	0.739***	0.350**	0.779***
	(2.06)	(6.11)	(1.91)	(5.97)	(1.60)	(5.56)	(1.96)	(5.65)
9	0.689***	1.131***	0.378**	0.755***	0.442***	0.865***	0.582***	0.989***
	(4.24)	(9.32)	(2.46)	(6.44)	(2.67)	(6.87)	(3.77)	(8.32)
High	0.563***	0.870***	0.444***	0.819***	0.717***	1.045***	0.414***	0.772***
	(4.11)	(8.18)	(3.04)	(6.89)	(4.28)	(8.07)	(3.17)	(7.35)
H-L	0.923***	0.834***	0.392***	0.326***	0.920***	0.901***	0.388**	0.293*
	(7.13)	(6.54)	(3.34)	(2.76)	(6.79)	(6.67)	(2.58)	(1.91)

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Panel B: MA(50)

	PIN		PIN_B		PIN_G		AdjPIN	
Decile	$R^d_{j,m,50}$	α_j	$R^d_{j,m,50}$	α_j	$R^d_{j,m,50}$	α_j	$R^d_{j,m,50}$	α_j
Low	-0.148	0.207*	-0.111	0.383***	-0.158	0.229*	-0.170	0.287**
	(-1.03)	(1.72)	(-0.62)	(2.68)	(-1.03)	(1.79)	(-1.02)	(2.12)
2	-0.112	0.320**	-0.112	0.372***	-0.074	0.351**	-0.198	0.288**
	(-0.70)	(2.47)	(-0.64)	(2.69)	(-0.43)	(2.39)	(-1.19)	(2.12)
3	-0.091	0.397***	-0.029	0.459***	-0.089	0.372***	-0.068	0.390***
	(-0.51)	(2.69)	(-0.16)	(3.34)	(-0.52)	(2.65)	(-0.40)	(2.88)
4	-0.054	0.422***	0.115	0.638***	0.005	0.487***	-0.066	0.420***
	(-0.28)	(2.63)	(0.63)	(4.61)	(0.03)	(3.49)	(-0.36)	(2.86)
5	-0.053	0.434***	0.010	0.523***	-0.054	0.418***	0.026	0.514***
	(-0.29)	(3.11)	(0.05)	(3.80)	(-0.32)	(3.16)	(0.13)	(3.43)
6	-0.047	0.413***	-0.023	0.436***	0.021	0.466***	-0.004	0.469***
	(-0.25)	(2.82)	(-0.13)	(3.16)	(0.12)	(3.51)	(-0.02)	(3.13)
7	0.081	0.547***	0.076	0.506***	0.030	0.507***	0.019	0.482***
	(0.42)	(3.70)	(0.45)	(3.99)	(0.16)	(3.58)	(0.10)	(3.49)
8	0.121	0.601***	0.098	0.526***	0.125	0.615***	0.199	0.667***
	(0.64)	(4.15)	(0.58)	(4.01)	(0.73)	(4.80)	(1.04)	(4.44)
9	0.321*	0.761***	-0.002	0.387***	0.182	0.616***	0.262	0.683***
	(1.90)	(5.99)	(-0.01)	(3.26)	(1.07)	(4.81)	(1.61)	(5.44)
High	0.278**	0.648***	0.035	0.414***	0.420**	0.836***	0.093	0.407***
	(2.05)	(6.29)	(0.24)	(3.64)	(2.54)	(7.03)	(0.76)	(4.16)
H-L	0.427***	0.441***	0.146	0.030	0.577***	0.608***	0.263**	0.120
	(3.78)	(3.91)	(1.47)	(0.29)	(4.97)	(5.28)	(2.44)	(1.10)

Table 6: Trading, Holding, and Costs

This tables reports the average holding days (Holding) and number of trades per year, as well as break-even transaction costs of MA(10) and MA(50) strategies, for the portfolios formed by PIN, PIN_B, PIN_G, and adjusted PIN.

	PIN			PIN_B			PIN_G			AdjPIN		
Decile	Holding	Trades	BETC	Holding	Trades	BETC	Holding	Trades	BETC	Holding	Trades	BETC
Panel A: MA(10)												
Low	229.3	40.5	0.443	220.4	38.3	0.626	231.9	38.9	0.694	224.6	40.0	0.641
2	226.5	39.4	0.504	222.9	39.0	0.634	223.7	40.6	0.561	225.7	39.0	0.558
3	223.4	39.1	0.608	222.2	37.1	0.710	225.1	38.6	0.616	224.8	37.4	0.605
4	219.6	38.2	0.673	224.0	38.1	0.710	223.6	39.0	0.709	220.0	39.7	0.647
5	222.9	38.1	0.817	221.9	36.9	0.739	224.3	36.1	0.813	220.7	38.1	0.763
6	221.2	36.8	0.877	223.8	37.9	0.808	222.9	37.7	0.820	219.2	36.8	0.885
7	222.7	35.9	1.084	222.2	37.0	0.910	221.8	35.3	0.994	220.1	36.7	0.929
8	223.3	35.1	1.236	226.6	34.7	1.174	224.6	35.4	1.076	223.8	36.0	1.124
9	227.0	30.3	1.592	231.4	33.6	1.336	223.7	33.5	1.229	228.7	32.4	1.398
High	232.7	32.6	1.413	236.1	33.9	1.361	225.3	31.5	1.397	240.6	30.7	1.499
Panel B: MA(50)												
Low	263.1	14.6	1.362	246.3	14.9	1.386	261.0	13.4	1.911	257.1	15.7	1.457
2	257.8	15.4	1.230	254.9	15.1	1.318	256.5	14.6	1.574	256.2	15.2	1.285
3	254.0	14.7	1.335	246.7	14.5	1.497	254.0	14.6	1.548	251.9	14.1	1.520
4	249.6	15.1	1.425	250.9	13.9	1.708	253.2	13.9	1.835	248.2	15.6	1.441
5	246.2	14.5	1.730	247.3	13.1	1.792	251.3	14.6	1.717	245.6	14.8	1.612
6	247.1	13.2	2.103	247.1	13.3	2.056	246.4	13.4	2.028	243.1	13.9	1.964
7	240.8	12.8	2.600	248.4	13.1	2.362	246.6	13.9	2.180	244.3	13.2	2.213
8	242.4	12.3	3.074	250.9	11.7	3.160	246.0	12.5	2.567	243.9	11.4	3.018
9	243.6	10.4	4.062	255.5	12.8	3.059	244.8	11.5	2.955	246.3	10.1	4.018
High	251.5	9.6	4.438	259.2	11.4	3.682	242.1	9.9	3.919	260.1	9.2	4.637

Table 7: Two-Way Classification: Market Value vs. Information Measures

Stocks are sorted independently by the firm sizes in year $n-1$ and information measures estimated in that year. Then five-by-five portfolios are formed and their equally-weighted returns are use to perform MA strategies. This table reports the performance of PIN-MV portfolios with both MA(10) and MA(50) strategies, as well as those for PIN_B-MV, PIN_G-MV, and Adjusted-PIN-MV portfolios with the MA(10) strategies. For each strategy, the return differences $R^d_{j,m,10}$, their alphas for the six-factor model and t-values (in parentheses) are reported. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively.

	$R^d_{j,m,L}$					α_j				
MV	Small	2	3	4	Large	Small	2	3	4	Large
Panel A: MA(10) of PIN										
Low	-1.090***	-0.771**	-0.373*	0.012	-0.316**	-0.678	-0.446	0.171	0.520***	0.122
	(-2.71)	(-2.57)	(-1.66)	(0.06)	(-2.18)	(-1.63)	(-1.52)	(0.88)	(3.71)	(1.08)
2	-1.216***	-0.258	0.143	0.149	-0.215	-1.131**	0.132	0.672***	0.696***	0.221
	(-2.88)	(-1.02)	(0.65)	(0.77)	(-1.26)	(-2.52)	(0.58)	(3.78)	(4.57)	(1.60)
3	-0.534*	0.339	0.111	0.092	-0.078	-0.303	0.917***	0.590***	0.592***	0.357**
	(-1.74)	(1.47)	(0.56)	(0.49)	(-0.43)	(-1.01)	(5.34)	(3.93)	(3.89)	(2.51)
4	0.273	0.124	0.150	0.286	0.095	0.768***	0.610***	0.687***	0.772***	0.324*
	(1.32)	(0.60)	(0.73)	(1.42)	(0.46)	(4.39)	(3.75)	(4.05)	(4.91)	(1.91)
High	0.551***	0.345**	0.274	0.089	0.230	0.916***	0.809***	0.764***	0.446**	0.618***
	(3.71)	(1.99)	(1.32)	(0.44)	(1.00)	(7.59)	(6.00)	(4.42)	(2.58)	(3.48)
Panel B: MA(50) of PIN										
Low	-0.129	-0.428	-0.161	-0.024	-0.214	0.284	-0.150	0.408**	0.434***	0.183
	(-0.35)	(-1.34)	(-0.73)	(-0.13)	(-1.48)	(0.75)	(-0.49)	(2.29)	(3.02)	(1.54)
2	-0.479	-0.314	0.146	-0.023	-0.235	-0.559	0.265	0.760***	0.541***	0.188
	(-1.18)	(-1.24)	(0.69)	(-0.12)	(-1.45)	(-1.29)	(1.22)	(4.58)	(3.87)	(1.43)
3	-0.006	0.052	0.039	-0.128	-0.191	0.259	0.594***	0.580***	0.370**	0.261*
	(-0.02)	(0.23)	(0.18)	(-0.68)	(-1.07)	(1.01)	(3.26)	(3.68)	(2.39)	(1.76)
4	0.209	0.259	-0.018	0.000	-0.037	0.627***	0.753***	0.545***	0.473***	0.199
	(1.05)	(1.30)	(-0.08)	(0.00)	(-0.16)	(3.70)	(5.00)	(3.26)	(2.96)	(1.03)
High	0.241*	0.252	0.129	-0.228	-0.034	0.556***	0.744***	0.655***	0.184	0.533***
	(1.72)	(1.44)	(0.60)	(-1.07)	(-0.13)	(4.92)	(5.60)	(3.72)	(0.99)	(2.66)

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	$R^d_{j,m,L}$					α_j				
MV	Small	2	3	4	Large	Small	2	3	4	Large
Panel C: MA(10) of PIN_B										
Low	-0.294	0.219	0.168	0.018	-0.319*	0.271	0.587***	0.653***	0.512***	0.085
	(-1.09)	(0.89)	(0.78)	(0.09)	(-1.95)	(1.06)	(2.97)	(3.87)	(3.29)	(0.65)
2	0.030	0.294	0.229	0.160	-0.258*	0.461**	0.843***	0.720***	0.684***	0.154
	(0.12)	(1.24)	(1.04)	(0.84)	(-1.71)	(2.16)	(4.46)	(4.10)	(4.66)	(1.30)
3	0.254	0.364*	0.076	0.086	-0.247	0.642***	0.874***	0.597***	0.646***	0.209*
	(1.29)	(1.70)	(0.37)	(0.46)	(-1.63)	(3.93)	(5.34)	(3.69)	(4.45)	(1.73)
4	0.166	0.114	0.030	-0.002	-0.137	0.578***	0.566***	0.547***	0.486***	0.324**
	(0.96)	(0.56)	(0.14)	(-0.01)	(-0.85)	(3.89)	(3.41)	(3.15)	(3.25)	(2.54)
High	0.010	0.108	-0.025	-0.032	-0.054	0.332***	0.532***	0.514***	0.444***	0.332**
	(0.07)	(0.65)	(-0.12)	(-0.17)	(-0.29)	(2.78)	(4.11)	(3.22)	(2.87)	(2.25)
Panel D: MA(10) of PIN_G										
Low	-0.709***	-0.648***	-0.212	0.026	-0.387***	-0.316	-0.312	0.334**	0.510***	0.014
	(-3.14)	(-2.61)	(-1.03)	(0.14)	(-2.62)	(-1.40)	(-1.36)	(2.01)	(3.60)	(0.12)
2	-0.914***	-0.191	-0.061	-0.038	-0.272*	-0.503**	0.315*	0.474***	0.515***	0.212*
	(-4.37)	(-0.90)	(-0.29)	(-0.20)	(-1.74)	(-2.52)	(1.76)	(2.78)	(3.55)	(1.78)
3	-0.316*	-0.019	0.074	0.200	-0.222	0.004	0.451***	0.603***	0.718***	0.212*
	(-1.73)	(-0.08)	(0.37)	(1.03)	(-1.38)	(0.02)	(2.66)	(3.90)	(4.71)	(1.67)
4	0.311*	0.301	0.201	0.158	-0.219	0.749***	0.883***	0.755***	0.652***	0.131
	(1.72)	(1.40)	(0.97)	(0.80)	(-1.16)	(4.74)	(5.27)	(4.73)	(4.22)	(0.81)
High	0.617***	0.686***	0.218	0.207	-0.067	0.990***	1.167***	0.688***	0.634***	0.267
	(3.88)	(3.45)	(1.04)	(1.01)	(-0.33)	(7.70)	(7.36)	(4.09)	(3.96)	(1.63)
Panel E: MA(10) of AdjPIN										
Low	-1.025***	-0.109	0.220	0.064	-0.306**	-0.641**	0.375*	0.745***	0.565***	0.121
	(-3.75)	(-0.40)	(1.05)	(0.34)	(-2.10)	(-2.52)	(1.74)	(4.32)	(3.81)	(1.08)
2	-0.269	-0.192	0.175	0.098	-0.271*	0.003	0.224	0.714***	0.608***	0.181
	(-0.53)	(-0.72)	(0.84)	(0.51)	(-1.69)	(0.00)	(0.97)	(4.38)	(3.98)	(1.44)
3	-0.684*	0.101	0.136	0.077	-0.095	-0.468	0.651***	0.690***	0.621***	0.378***
	(-1.67)	(0.41)	(0.63)	(0.40)	(-0.57)	(-1.12)	(3.42)	(3.96)	(4.24)	(2.92)
4	0.042	0.154	0.062	0.081	-0.023	0.480***	0.677***	0.586***	0.515***	0.418***
	(0.21)	(0.73)	(0.30)	(0.43)	(-0.11)	(2.96)	(4.13)	(3.57)	(3.31)	(2.72)
High	0.345**	0.274*	0.066	-0.053	0.155	0.707***	0.685***	0.528***	0.369**	0.722**
	(2.38)	(1.69)	(0.36)	(-0.26)	(0.47)	(5.78)	(5.35)	(3.46)	(2.08)	(2.38)

Table 8: Two-Way Classification: Return Volatility vs. Information Measures

Stocks are sorted independently by the standard deviations of daily returns (std) in year $n-1$ and information measures estimated in that year. Then five-by-five portfolios are formed and their equally-weighted returns are use to perform MA strategies. This table reports the performance of PIN-std portfolios with both MA(10) and MA(50) strategies, as well as those for PIN_B-std, PIN_G-std, and Adjusted-PIN-std portfolios with the MA(10) strategies. For each strategy, the return differences $R^d_{j,m,10}$, their alphas for the six-factor model and t-values (in parentheses) are reported. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively.

	$R^d_{j,m,L}$					α_j				
Std.	Low	2	3	4	High	Low	2	3	4	High
Panel A: MA(10) of PIN										
Low	-0.276***	-0.321**	-0.098	-0.004	-0.476*	0.009	0.130	0.456***	0.580***	0.043
	(-2.75)	(-2.28)	(-0.56)	(-0.01)	(-1.73)	(0.09)	(1.14)	(3.48)	(3.66)	(0.18)
2	-0.246**	-0.224	0.092	0.300	-0.110	0.070	0.242**	0.611***	0.923***	0.437*
	(-2.05)	(-1.50)	(0.48)	(1.32)	(-0.40)	(0.61)	(1.99)	(4.11)	(5.40)	(1.88)
3	-0.102	-0.147	0.011	0.183	0.519**	0.259**	0.286**	0.513***	0.775***	1.070***
	(-0.80)	(-1.02)	(0.05)	(0.85)	(2.10)	(2.29)	(2.44)	(3.49)	(4.68)	(5.47)
4	0.060	0.057	0.100	0.262	0.321	0.407***	0.441***	0.546***	0.748***	0.832***
	(0.51)	(0.39)	(0.57)	(1.31)	(1.39)	(4.07)	(3.70)	(3.91)	(4.77)	(4.51)
High	0.232*	0.145	0.496***	0.640***	0.519***	0.622***	0.526***	0.908***	1.035***	0.924***
	(1.96)	(1.06)	(3.54)	(3.66)	(2.81)	(6.29)	(4.60)	(7.99)	(7.70)	(6.15)
Panel B: MA(50) of PIN										
Low	-0.227**	-0.231*	-0.169	-0.185	-0.211	-0.015	0.212*	0.381***	0.325*	0.234
	(-2.32)	(-1.68)	(-0.96)	(-0.86)	(-0.74)	(-0.16)	(1.91)	(2.71)	(1.84)	(0.95)
2	-0.198**	-0.174	0.016	0.048	-0.005	0.066	0.232**	0.566***	0.680***	0.516**
	(-2.09)	(-1.25)	(0.08)	(0.21)	(-0.01)	(0.76)	(2.04)	(4.04)	(3.92)	(2.38)
3	-0.002	-0.139	0.015	0.027	0.147	0.319***	0.248**	0.513***	0.602***	0.623***
	(-0.02)	(-1.04)	(0.08)	(0.12)	(0.58)	(3.37)	(2.22)	(3.62)	(3.50)	(3.13)
4	-0.007	-0.036	0.071	0.185	0.196	0.259***	0.345***	0.562***	0.703***	0.699***
	(-0.06)	(-0.27)	(0.42)	(0.93)	(0.81)	(2.59)	(3.14)	(4.33)	(4.61)	(3.65)
High	0.175	0.146	0.303**	0.433**	0.194	0.551***	0.531***	0.718***	0.868***	0.556***
	(1.50)	(1.14)	(2.11)	(2.42)	(1.10)	(5.60)	(5.07)	(6.49)	(6.36)	(3.92)

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	$R^d_{j,m,L}$					α_j				
Std.	Low	2	3	4	High	Low	2	3	4	High
Panel C: MA(10) of PIN_B										
Low	-0.234**	-0.226	-0.028	0.156	0.238	0.086	0.249*	0.486***	0.667***	0.843***
	(-2.17)	(-1.49)	(-0.15)	(0.71)	(0.90)	(0.85)	(1.95)	(3.23)	(3.88)	(4.20)
2	-0.285***	-0.270*	0.051	0.257	0.367	-0.011	0.169	0.577***	0.813***	0.899***
	(-2.73)	(-1.87)	(0.28)	(1.14)	(1.44)	(-0.11)	(1.47)	(4.20)	(4.83)	(4.36)
3	-0.234**	-0.168	0.160	0.222	0.565**	0.123	0.245**	0.736***	0.762***	1.104***
	(-2.01)	(-1.24)	(0.87)	(1.07)	(2.41)	(1.18)	(2.20)	(5.22)	(4.71)	(5.97)
4	-0.065	-0.108	0.200	0.261	0.375*	0.237**	0.309***	0.703***	0.763***	0.822***
	(-0.58)	(-0.77)	(1.10)	(1.26)	(1.73)	(2.32)	(2.67)	(4.87)	(4.51)	(4.50)
High	0.149	0.138	0.268*	0.505***	-0.000	0.473***	0.521***	0.708***	0.991***	0.395**
	(1.38)	(0.97)	(1.71)	(2.87)	(-0.00)	(5.13)	(4.27)	(5.89)	(7.39)	(2.48)
Panel D: MA(10) of PIN_G										
Low	-0.324***	-0.410***	-0.005	0.223	-0.419*	-0.052	-0.024	0.514***	0.817***	0.072
	(-3.23)	(-2.97)	(-0.02)	(1.03)	(-1.69)	(-0.55)	(-0.19)	(3.82)	(5.12)	(0.34)
2	-0.129	-0.192	-0.058	0.124	0.118	0.203**	0.291**	0.504***	0.681***	0.627***
	(-1.18)	(-1.32)	(-0.31)	(0.60)	(0.47)	(2.02)	(2.45)	(3.56)	(4.35)	(2.87)
3	-0.010	-0.127	0.149	0.252	0.266	0.334***	0.313***	0.694***	0.787***	0.717***
	(-0.08)	(-0.88)	(0.86)	(1.21)	(1.17)	(2.87)	(2.63)	(5.31)	(4.92)	(3.95)
4	-0.014	-0.033	0.227	0.276	0.424*	0.312***	0.387***	0.725***	0.821***	0.944***
	(-0.11)	(-0.21)	(1.28)	(1.32)	(1.91)	(3.00)	(3.00)	(5.29)	(5.17)	(5.45)
High	0.188	0.089	0.290*	0.673***	0.704***	0.576***	0.460***	0.638***	1.134***	1.183***
	(1.44)	(0.70)	(1.81)	(3.48)	(3.49)	(4.98)	(4.35)	(4.76)	(7.59)	(7.64)
Panel E: MA(10) of AdjPIN										
Low	-0.271***	-0.326**	-0.058	0.228	-0.210	-0.014	0.136	0.498***	0.823***	0.297
	(-2.66)	(-2.38)	(-0.32)	(1.04)	(-0.43)	(-0.14)	(1.21)	(3.49)	(4.98)	(0.62)
2	-0.256**	-0.188	0.040	0.246	0.377	0.074	0.271**	0.566***	0.763***	0.908***
	(-2.24)	(-1.24)	(0.21)	(1.18)	(1.38)	(0.68)	(2.14)	(4.07)	(4.83)	(4.09)
3	-0.179	-0.166	0.009	0.182	0.406	0.160	0.277**	0.504***	0.789***	1.049***
	(-1.47)	(-1.16)	(0.04)	(0.80)	(1.51)	(1.47)	(2.35)	(3.47)	(4.56)	(4.95)
4	-0.029	-0.034	0.040	0.277	0.324	0.315**	0.394***	0.529***	0.768***	0.827***
	(-0.19)	(-0.22)	(0.22)	(1.33)	(1.39)	(2.27)	(3.11)	(3.75)	(4.69)	(4.49)
High	0.141	0.197	0.504***	0.489***	0.201	0.496***	0.558***	0.917***	0.944***	0.584***
	(1.23)	(1.44)	(3.38)	(2.79)	(1.15)	(5.01)	(4.87)	(7.43)	(6.87)	(3.86)

Table 9: Two-Way Classification: Income Volatility vs. Information Measures

Stocks are sorted independently by the standard deviation of quarterly operating income (IVOL) between year $n-1$ and $n-5$ and information measures estimated in year $n-1$. Then five-by-five portfolios are formed and their equally-weighted returns are use to perform MA strategies. This table reports the performance of PIN-IVOL portfolios with both MA(10) and MA(50) strategies, as well as those for PIN_B-IVOL, PIN_G-IVOL, and Adjusted-PIN-IVOL portfolios with the MA(10) strategies. For each strategy, the return differences $R^d_{j,m,10}$, their alphas for the six-factor model and t-values (in parentheses) are reported. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively.

	$R^d_{j,m,L}$					α_j				
IVOL	Low	2	3	4	High	Low	2	3	4	High
Panel A: MA(10) of PIN										
Low	-0.423***	-0.363**	-0.293**	-0.369**	-0.436**	-0.012	0.031	0.161	0.119	0.064
	(-2.78)	(-2.38)	(-1.98)	(-2.27)	(-2.23)	(-0.09)	(0.24)	(1.35)	(0.92)	(0.38)
2	-0.080	0.021	-0.091	-0.047	-0.104	0.448***	0.533***	0.382**	0.476***	0.388**
	(-0.43)	(0.11)	(-0.49)	(-0.25)	(-0.50)	(3.12)	(3.69)	(2.56)	(3.12)	(2.24)
3	-0.049	-0.103	0.046	0.022	0.126	0.426***	0.416***	0.599***	0.508***	0.641***
	(-0.27)	(-0.54)	(0.24)	(0.11)	(0.59)	(2.92)	(2.76)	(4.14)	(3.21)	(3.70)
4	-0.034	0.125	0.053	0.098	0.314	0.407***	0.549***	0.613***	0.639***	0.787***
	(-0.18)	(0.66)	(0.26)	(0.49)	(1.47)	(2.64)	(3.45)	(3.92)	(3.96)	(4.51)
High	0.164	0.053	0.315**	0.383**	0.191	0.594***	0.424***	0.788***	0.823***	0.531***
	(1.04)	(0.30)	(1.97)	(2.34)	(1.08)	(4.81)	(3.03)	(6.25)	(6.11)	(3.48)
Panel B: MA(50) of PIN										
Low	-0.271*	-0.168	-0.208	-0.267	-0.108	0.147	0.222*	0.188	0.201	0.319**
	(-1.86)	(-1.15)	(-1.38)	(-1.56)	(-0.57)	(1.20)	(1.81)	(1.50)	(1.43)	(1.98)
2	-0.111	-0.155	-0.075	-0.029	-0.183	0.416***	0.365**	0.399***	0.509***	0.263*
	(-0.60)	(-0.86)	(-0.41)	(-0.15)	(-0.95)	(2.84)	(2.51)	(2.68)	(3.29)	(1.65)
3	-0.119	0.042	-0.030	-0.147	-0.082	0.382***	0.538***	0.507***	0.285*	0.403**
	(-0.66)	(0.22)	(-0.15)	(-0.77)	(-0.39)	(2.59)	(3.72)	(3.37)	(1.79)	(2.32)
4	-0.199	0.125	0.102	0.017	0.250	0.277*	0.564***	0.611***	0.490***	0.716***
	(-1.05)	(0.70)	(0.52)	(0.08)	(1.22)	(1.72)	(3.96)	(3.98)	(3.02)	(4.29)
High	0.220	0.075	0.188	0.132	0.091	0.685***	0.485***	0.693***	0.465***	0.370**
	(1.40)	(0.47)	(1.13)	(0.84)	(0.52)	(5.52)	(3.72)	(5.29)	(3.55)	(2.52)

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	$R^d_{j,m,L}$					α_j				
IVOL	Low	2	3	4	High	Low	2	3	4	High
Panel C: MA(10) of PIN_B										
Low	-0.141	-0.150	-0.137	0.000	0.136	0.297**	0.319**	0.360**	0.544***	0.617***
	(-0.76)	(-0.82)	(-0.76)	(0.00)	(0.65)	(2.06)	(2.13)	(2.49)	(3.91)	(3.64)
2	-0.208	-0.142	-0.072	0.163	0.199	0.246*	0.334**	0.421***	0.650***	0.742***
	(-1.18)	(-0.79)	(-0.40)	(0.90)	(0.90)	(1.76)	(2.36)	(3.04)	(4.63)	(4.35)
3	-0.138	-0.127	0.057	0.026	0.213	0.403***	0.372***	0.579***	0.527***	0.778***
	(-0.82)	(-0.78)	(0.33)	(0.14)	(1.05)	(3.12)	(2.91)	(4.39)	(3.71)	(4.87)
4	-0.073	0.007	-0.049	-0.061	0.231	0.414***	0.471***	0.460***	0.367**	0.660***
	(-0.42)	(0.03)	(-0.29)	(-0.33)	(1.30)	(2.93)	(3.31)	(3.44)	(2.31)	(4.54)
High	0.029	-0.169	-0.130	0.074	-0.284*	0.463***	0.283**	0.306**	0.514***	0.027
	(0.17)	(-0.95)	(-0.79)	(0.46)	(-1.72)	(3.60)	(1.97)	(2.29)	(4.02)	(0.17)
Panel D: MA(10) of PIN_G										
Low	-0.446***	-0.144	-0.343**	-0.314*	-0.525***	-0.101	0.285**	0.063	0.168	-0.063
	(-2.97)	(-0.84)	(-2.29)	(-1.87)	(-2.80)	(-0.80)	(2.04)	(0.52)	(1.17)	(-0.39)
2	-0.192	-0.120	-0.059	-0.169	-0.312	0.309**	0.401***	0.487***	0.337**	0.215
	(-1.15)	(-0.70)	(-0.33)	(-0.92)	(-1.57)	(2.36)	(3.01)	(3.43)	(2.26)	(1.26)
3	-0.120	-0.143	-0.015	-0.040	0.084	0.384***	0.357**	0.470***	0.463***	0.515***
	(-0.65)	(-0.78)	(-0.08)	(-0.23)	(0.45)	(2.62)	(2.46)	(3.16)	(3.52)	(3.40)
4	-0.066	0.069	0.151	0.220	0.232	0.451***	0.534***	0.658***	0.688***	0.768***
	(-0.34)	(0.39)	(0.77)	(1.15)	(1.20)	(3.01)	(3.79)	(4.22)	(4.60)	(4.88)
High	0.071	0.128	0.374**	0.380**	0.442**	0.409***	0.508***	0.876***	0.850***	0.862***
	(0.42)	(0.74)	(2.20)	(2.21)	(2.23)	(2.93)	(3.61)	(6.60)	(6.29)	(5.52)
Panel E: MA(10) of AdjPIN										
Low	-0.305*	-0.135	-0.280*	-0.642	-0.204	0.091	0.328**	0.231*	-0.127	0.310*
	(-1.86)	(-0.84)	(-1.71)	(-1.55)	(-0.99)	(0.69)	(2.56)	(1.78)	(-0.30)	(1.83)
2	-0.083	-0.156	-0.058	-0.063	-0.140	0.360***	0.346**	0.421***	0.421***	0.368**
	(-0.47)	(-0.90)	(-0.32)	(-0.36)	(-0.69)	(2.65)	(2.58)	(2.89)	(2.95)	(2.21)
3	-0.076	0.017	0.045	0.133	0.069	0.416***	0.503***	0.644***	0.680***	0.609***
	(-0.41)	(0.08)	(0.23)	(0.67)	(0.32)	(2.75)	(3.27)	(4.44)	(4.38)	(3.51)
4	-0.109	-0.058	0.104	0.132	0.167	0.336**	0.430***	0.617***	0.660***	0.684***
	(-0.59)	(-0.32)	(0.54)	(0.70)	(0.78)	(2.11)	(2.90)	(4.04)	(4.46)	(3.98)
High	0.107	-0.061	0.257	0.145	0.040	0.475***	0.293*	0.678***	0.585***	0.400***
	(0.73)	(-0.33)	(1.58)	(0.89)	(0.24)	(3.95)	(1.89)	(5.24)	(4.19)	(2.78)

Table 10: Two-Way Classification: Analyst Coverage vs. Information Measures

Stocks are sorted independently by the number of analysts covering the firm (cover) in year $n-1$ and information measures estimated in that year. Then five-by-five portfolios are formed and their equally-weighted returns are use to perform MA strategies. This table reports the performance of PIN-cover portfolios with both MA(10) and MA(50) strategies, as well as those for PIN_B-cover, PIN_G-cover, and Adjusted-PIN-cover portfolios with the MA(10) strategies. For each strategy, the return differences $R^d_{j,m,10}$, their alphas for the six-factor model and t-values (in parentheses) are reported. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively.

	$R^d_{j,m,L}$					α_j				
Cover	Least	2	3	4	Most	Least	2	3	4	Most
Panel A: MA(10)										
Low	-0.864***	-0.217	-0.039	-0.163	-0.383**	-0.532**	0.264*	0.437***	0.338**	0.069
	(-3.52)	(-1.17)	(-0.21)	(-0.96)	(-2.56)	(-2.32)	(1.80)	(2.96)	(2.50)	(0.58)
2	-0.084	-0.101	0.127	-0.003	-0.060	0.395**	0.431***	0.656***	0.587***	0.406***
	(-0.37)	(-0.49)	(0.61)	(-0.01)	(-0.34)	(2.11)	(2.61)	(4.05)	(4.08)	(3.10)
3	-0.114	0.052	0.018	0.035	-0.096	0.360**	0.618***	0.554***	0.574***	0.313*
	(-0.52)	(0.25)	(0.09)	(0.17)	(-0.49)	(2.03)	(3.99)	(3.60)	(3.58)	(1.95)
4	0.233	0.223	0.384*	0.257	-0.156	0.703***	0.752***	0.924***	0.741***	0.138
	(1.24)	(1.10)	(1.89)	(1.21)	(-0.68)	(4.70)	(4.78)	(5.66)	(4.33)	(0.68)
High	0.385**	0.478**	0.443*	0.357	-0.118	0.860***	0.934***	1.015***	0.882***	0.149
	(2.28)	(2.44)	(1.95)	(1.37)	(-0.37)	(6.54)	(5.99)	(5.45)	(3.98)	(0.52)
Panel B: MA(50)										
Low	-0.466**	-0.166	-0.159	-0.223	-0.293*	-0.091	0.254	0.292*	0.203	0.104
	(-1.97)	(-0.89)	(-0.86)	(-1.36)	(-1.94)	(-0.41)	(1.61)	(1.92)	(1.48)	(0.82)
2	-0.103	-0.099	-0.025	-0.053	-0.276	0.372**	0.388**	0.546***	0.529***	0.149
	(-0.48)	(-0.47)	(-0.12)	(-0.29)	(-1.59)	(2.04)	(2.29)	(3.52)	(3.84)	(1.06)
3	-0.087	0.015	-0.002	-0.158	-0.069	0.388**	0.528***	0.582***	0.324**	0.316**
	(-0.41)	(0.07)	(-0.00)	(-0.79)	(-0.36)	(2.28)	(3.34)	(3.74)	(1.98)	(2.11)
4	0.123	0.027	0.051	0.104	-0.216	0.582***	0.613***	0.547***	0.644***	-0.015
	(0.65)	(0.13)	(0.21)	(0.47)	(-0.87)	(3.88)	(3.97)	(2.78)	(3.62)	(-0.06)
High	0.221	0.453**	0.054	0.172	0.128	0.618***	0.998***	0.684***	0.673***	0.548*
	(1.32)	(2.27)	(0.22)	(0.66)	(0.36)	(4.68)	(6.39)	(3.79)	(3.02)	(1.74)

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	$R^d_{j,m,L}$					α_j				
Cover	Least	2	3	4	Most	Least	2	3	4	Most
Panel C: MA(10) of PIN_B										
Low	0.135	0.177	0.024	0.001	-0.365**	0.591***	0.687***	0.491***	0.565***	0.103
	(0.60)	(0.82)	(0.11)	(0.00)	(-2.19)	(3.32)	(3.98)	(2.96)	(3.80)	(0.78)
2	0.192	0.272	0.198	0.107	-0.310*	0.745***	0.786***	0.711***	0.656***	0.105
	(0.85)	(1.31)	(1.00)	(0.57)	(-1.95)	(4.26)	(4.97)	(4.58)	(4.51)	(0.82)
3	0.069	0.085	0.207	0.117	-0.228	0.475***	0.637***	0.765***	0.664***	0.234*
	(0.34)	(0.42)	(1.04)	(0.64)	(-1.46)	(2.99)	(4.23)	(5.11)	(4.76)	(1.93)
4	0.009	0.242	0.138	0.001	-0.079	0.469***	0.770***	0.680***	0.550***	0.342**
	(0.04)	(1.29)	(0.68)	(0.00)	(-0.44)	(3.22)	(5.22)	(4.24)	(3.75)	(2.31)
High	0.005	0.063	0.215	0.240	-0.297	0.488***	0.484***	0.762***	0.750***	0.064
	(0.02)	(0.35)	(1.05)	(1.17)	(-1.49)	(3.66)	(3.38)	(4.79)	(4.65)	(0.38)
Panel D: MA(10) of PIN_G										
Low	-0.773***	-0.059	-0.057	-0.067	-0.317**	-0.303	0.392***	0.438***	0.413***	0.122
	(-3.48)	(-0.32)	(-0.28)	(-0.40)	(-2.12)	(-1.56)	(2.68)	(2.66)	(3.14)	(1.11)
2	-0.350*	-0.055	0.098	-0.005	-0.239	0.064	0.446***	0.644***	0.589***	0.225*
	(-1.85)	(-0.27)	(0.51)	(-0.02)	(-1.52)	(0.38)	(2.86)	(4.27)	(4.16)	(1.84)
3	-0.024	0.104	0.076	0.131	-0.146	0.438***	0.590***	0.583***	0.705***	0.315**
	(-0.12)	(0.54)	(0.39)	(0.65)	(-0.82)	(2.85)	(3.91)	(3.83)	(4.48)	(2.31)
4	0.187	0.226	0.157	0.231	-0.122	0.666***	0.793***	0.686***	0.810***	0.263*
	(0.93)	(1.17)	(0.72)	(1.23)	(-0.63)	(4.25)	(5.25)	(3.99)	(5.55)	(1.65)
High	0.583***	0.576***	0.341	0.144	-0.306	1.018***	1.097***	0.831***	0.595***	0.038
	(3.20)	(2.64)	(1.60)	(0.66)	(-1.39)	(7.24)	(6.62)	(5.09)	(3.42)	(0.20)
Panel E: MA(10) of AdjPIN										
Low	-1.067	0.017	0.068	-0.036	-0.335**	-0.557	0.524**	0.591***	0.474***	0.117
	(-1.25)	(0.07)	(0.33)	(-0.20)	(-2.20)	(-0.62)	(2.52)	(3.71)	(3.48)	(1.00)
2	0.175	-0.006	0.062	-0.006	-0.282*	0.651***	0.476***	0.532***	0.560***	0.165
	(0.75)	(-0.03)	(0.32)	(-0.03)	(-1.74)	(3.39)	(3.01)	(3.37)	(4.01)	(1.31)
3	-0.023	-0.074	0.129	0.197	0.042	0.488***	0.417***	0.593***	0.783***	0.553***
	(-0.11)	(-0.36)	(0.65)	(0.96)	(0.22)	(2.88)	(2.64)	(3.82)	(4.90)	(3.75)
4	-0.096	0.274	0.137	0.189	0.380	0.367**	0.812***	0.677***	0.745***	0.582
	(-0.50)	(1.33)	(0.65)	(0.96)	(0.98)	(2.38)	(5.04)	(4.16)	(4.82)	(1.53)
High	0.365**	0.341*	0.163	-0.392	0.021	0.813***	0.784***	0.713***	-0.101	0.303
	(2.29)	(1.85)	(0.68)	(-1.37)	(0.04)	(6.51)	(5.40)	(3.74)	(-0.37)	(0.70)

Table 11: Two-Way Classification: Forecast Dispersion vs. Information Measures

Stocks are sorted independently by the standard deviation of analysts' EPS forecasts (disp) in year $n-1$ and information measures estimated in that year. Then five-by-five portfolios are formed and their equally-weighted returns are use to perform MA strategies. This table reports the performance of PIN-disp portfolios with both MA(10) and MA(50) strategies, as well as those for PIN_B-disp, PIN_G-disp, and Adjusted-PIN-disp portfolios with the MA(10) strategies. For each strategy, the return differences $R^d_{j,m,10}$, their alphas for the six-factor model and t-values (in parentheses) are reported. One, two and three asterisks (*) indicate the t-statistics is significant at 0.1, 0.05 and 0.01 level, respectively.

	$R^d_{j,m,L}$					α_j				
Disp	Low	2	3	4	High	Low	2	3	4	High
Panel A: MA(10)										
Low	-0.454***	-0.329**	-0.221	-0.147	0.029	-0.084	0.126	0.199*	0.331**	0.566***
	(-3.21)	(-2.29)	(-1.52)	(-0.86)	(0.13)	(-0.70)	(1.10)	(1.73)	(2.45)	(3.32)
2	-0.266	-0.055	0.016	-0.041	0.348	0.144	0.415***	0.539***	0.505***	0.956***
	(-1.56)	(-0.34)	(0.08)	(-0.20)	(1.45)	(0.99)	(3.32)	(3.52)	(3.08)	(5.03)
3	-0.235	-0.149	-0.157	-0.049	0.184	0.152	0.331**	0.312**	0.499***	0.783***
	(-1.39)	(-0.84)	(-0.83)	(-0.26)	(0.79)	(1.07)	(2.31)	(2.05)	(3.24)	(4.49)
4	-0.274	-0.203	-0.031	0.052	0.065	0.154	0.229	0.444***	0.522***	0.658***
	(-1.49)	(-1.10)	(-0.16)	(0.25)	(0.28)	(0.98)	(1.47)	(2.93)	(3.21)	(3.51)
High	0.025	-0.025	0.119	0.092	-0.100	0.466***	0.362**	0.488***	0.559***	0.388**
	(0.12)	(-0.12)	(0.55)	(0.48)	(-0.46)	(2.70)	(2.33)	(2.60)	(3.75)	(2.09)
Panel B: MA(50)										
Low	-0.380***	-0.232	-0.205	-0.152	-0.143	-0.031	0.144	0.216*	0.319**	0.389*
	(-2.77)	(-1.63)	(-1.35)	(-0.85)	(-0.59)	(-0.25)	(1.20)	(1.73)	(2.17)	(1.95)
2	-0.268*	-0.142	-0.143	-0.135	0.140	0.123	0.331**	0.322**	0.399**	0.746***
	(-1.77)	(-0.87)	(-0.78)	(-0.70)	(0.61)	(0.93)	(2.58)	(2.12)	(2.56)	(4.17)
3	-0.206	-0.167	-0.135	-0.082	0.035	0.176	0.293*	0.369**	0.441***	0.656***
	(-1.37)	(-0.94)	(-0.73)	(-0.43)	(0.13)	(1.40)	(1.94)	(2.51)	(2.92)	(3.46)
4	-0.293*	-0.127	-0.111	0.026	-0.025	0.174	0.239	0.374**	0.512***	0.529***
	(-1.69)	(-0.70)	(-0.60)	(0.12)	(-0.10)	(1.16)	(1.50)	(2.47)	(2.85)	(2.73)
High	-0.045	-0.005	-0.070	-0.093	0.156	0.294*	0.469***	0.327*	0.312*	0.688***
	(-0.23)	(-0.02)	(-0.32)	(-0.45)	(0.72)	(1.78)	(2.75)	(1.71)	(1.69)	(3.88)

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	$R^d_{j,m,L}$					α_j				
Disp	Low	2	3	4	High	Low	2	3	4	High
Panel C: MA(10) for PIN_B										
Low	-0.446***	-0.210	-0.110	-0.103	0.088	-0.052	0.206	0.351**	0.420**	0.682***
	(-2.82)	(-1.32)	(-0.56)	(-0.52)	(0.36)	(-0.39)	(1.63)	(2.13)	(2.57)	(3.58)
2	-0.404**	-0.136	-0.205	0.068	0.285	0.022	0.370***	0.252*	0.640***	0.935***
	(-2.56)	(-0.81)	(-1.18)	(0.34)	(1.16)	(0.16)	(2.71)	(1.89)	(4.17)	(4.76)
3	-0.225	-0.120	-0.076	-0.104	0.180	0.183	0.409***	0.480***	0.396***	0.791***
	(-1.47)	(-0.71)	(-0.45)	(-0.58)	(0.78)	(1.42)	(3.08)	(3.67)	(2.79)	(4.33)
4	-0.270*	-0.307*	-0.157	-0.039	0.233	0.114	0.083	0.318**	0.523***	0.813***
	(-1.67)	(-1.87)	(-0.85)	(-0.20)	(1.07)	(0.84)	(0.59)	(2.13)	(3.49)	(4.81)
High	-0.113	-0.088	-0.088	-0.006	-0.314	0.330**	0.335**	0.371**	0.395***	0.260
	(-0.66)	(-0.47)	(-0.48)	(-0.03)	(-1.35)	(2.33)	(2.33)	(2.40)	(2.73)	(1.34)
Panel D: MA(10) for PIN_G										
Low	-0.486***	-0.238	-0.236	-0.146	0.030	-0.123	0.177	0.199	0.284**	0.590***
	(-3.19)	(-1.64)	(-1.53)	(-0.85)	(0.13)	(-0.94)	(1.55)	(1.60)	(2.04)	(3.20)
2	-0.267*	-0.267*	-0.244	-0.085	-0.051	0.154	0.230*	0.273*	0.455***	0.549***
	(-1.70)	(-1.69)	(-1.34)	(-0.47)	(-0.21)	(1.20)	(1.78)	(1.92)	(3.27)	(2.83)
3	-0.263	-0.207	-0.094	-0.109	0.355	0.147	0.247*	0.392***	0.402**	0.960***
	(-1.56)	(-1.23)	(-0.51)	(-0.54)	(1.57)	(1.04)	(1.83)	(2.65)	(2.50)	(5.42)
4	-0.171	-0.051	-0.168	0.040	0.205	0.314**	0.384**	0.259	0.651***	0.860***
	(-1.04)	(-0.27)	(-0.68)	(0.19)	(0.90)	(2.29)	(2.58)	(1.14)	(4.02)	(4.89)
High	-0.189	-0.069	-0.001	0.196	0.229	0.156	0.356**	0.498***	0.629***	0.672***
	(-1.03)	(-0.35)	(-0.00)	(0.96)	(1.08)	(1.02)	(2.33)	(2.99)	(3.81)	(3.88)
Panel E: MA(10) for AdjPIN										
Low	-0.409***	-0.291*	-0.129	-0.161	0.160	-0.007	0.128	0.334***	0.296**	0.727***
	(-2.72)	(-1.95)	(-0.80)	(-0.88)	(0.72)	(-0.05)	(1.11)	(2.62)	(2.01)	(4.14)
2	-0.395**	-0.116	-0.178	0.016	0.243	0.008	0.334***	0.278*	0.559***	0.862***
	(-2.49)	(-0.74)	(-0.96)	(0.08)	(0.97)	(0.05)	(2.59)	(1.79)	(3.85)	(4.24)
3	-0.234	-0.203	-0.044	-0.072	0.155	0.219	0.304**	0.482***	0.488***	0.751***
	(-1.43)	(-1.13)	(-0.23)	(-0.35)	(0.64)	(1.63)	(2.13)	(3.32)	(3.06)	(3.80)
4	-0.211	-0.157	-0.089	-0.141	0.010	0.215	0.337**	0.358**	0.374**	0.601***
	(-1.26)	(-0.91)	(-0.47)	(-0.71)	(0.04)	(1.60)	(2.34)	(2.39)	(2.41)	(3.00)
High	-0.129	-0.164	0.020	-0.054	-0.110	0.250	0.247	0.463**	0.339*	0.427**
	(-0.63)	(-0.71)	(0.08)	(-0.24)	(-0.52)	(1.40)	(1.14)	(2.27)	(1.82)	(2.42)

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