Journal of Banking and Finance 134 (2022) 106347

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

Information asymmetry and the profitability of technical analysis☆

Chiayu Hung, Hung-Neng Lai*

Department of Finance, National Central University, Jhongli District, Taoyuan City, 32001, Taiwan

ARTICLE INFO

Article history:
Received 31 August 2020
Accepted 25 October 2021
Available online 27 October 2021

Keywords:
Probability of informed trading
Technical analysis
Moving averages
Market efficiency

ABSTRACT

Do informed investors leave a trace in the market? This study shows that the portfolios composed of stocks with a high probability of informed trading (PIN) earn significantly higher returns under moving average strategies than a buy-and-hold strategy. The abnormal returns cannot be explained by a Fama-French five-factor model with an additional momentum factor or transaction costs and yet exists even after imposing delayed trades or controlling for firm size, volatility, and liquidity. Portfolios with alternative information asymmetry measures report similar albeit weaker results.

1. Introduction

Technical analysis predicts future market trends by using historical trading data and is a widely used approach in financial industry.[1] Trading-related web sites provide numerous readymade technical indicators, and commentators and analysts in the media frequently discuss technical signals. Such passion for technical analysis, however, has received mixed reactions in academia. In this study, we speculate that while technical analysis can be effective, their findings cannot be universally applied. We will explore to what extent the information asymmetry of trading affect the profitability of technical analysis.

The debate over technical analysis is often portrait as a battle on the efficient market hypothesis: behavioral finance wins if technical analysis is effective; otherwise market efficiency wins. The fact is that it has been recognized that return predictability is compatible with efficient markets (Cochrane, 2011). To explore the role of information in the market, for example, quite a few noisy rational expectation models are proposed to show that it is possible that prices are not fully revealing. When investors are risk averse and there are two or more random sources in the market, Grundy and McNichols (1989) and Brown and Jennings (1989) show that technical analysis is useful for investors to estimate security values, and Cespa and Vives (2011) show that it is rational to implement momentum or contrarian trading strategies.

Wang (1993) and Blume et al. (1994) further explore the usefulness of technical analysis in an information asymmetry environment. In Wang's model, the informed investors know the value of the dividend and the uninformed do not. Because the supply of the security is also random, the current price cannot reveal the two random variables separately. The informed investors' trading is partially reflected in the past prices, which help the uninformed learn more about the dividend. Blume et al.'s model assumes that both means and variances of the signals for prices are random, and as a result, investors' expected utilities will increase if they use historical prices to estimate the variances. Blume et al. further speculate that technical analysis is likely to be effective for the securities which are more affected by private information.

The theoretical works by Wang and Blume et al. suggest that technical analysis is effective in securities with more private information, and this paper will examine this conjecture empirically. We collect returns data for stocks traded on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) and assign them to portfolios with different levels of information asymmetry, proxied by the probability of informed trading (PIN) developed by Easley, O'Hara, and their co-authors.[2] We follow Han et al. (2013) to apply moving average (MA) strategies to PIN portfolios and compare their performance with those under the buy-and-hold strategy. To address the problems of return fat tails and multiple hypotheses testing, the standard deviations of portfolio return differences are computed from empirical distributions using the Politis and Romano (1994) approach,

☆ We thank Carol Alexander (the managing editor) and two anonymous referees for insightful suggestions. We are also very grateful for the inspiring comments made by Yin-Feng Gau, Yu-Chin Hsu, and Meng-Lan Yueh. This research is partially funded by the Ministry of Science and Technology of Taiwan (Project Number MOST107-2410-H-008-028).

* Corresponding author.
E-mail address: hnlai@cc.ncu.edu.tw (H.-N. Lai).

[1] See Menkhoff and Taylor (2007), Lo and Hasanhodzic (2009), Menkhoff (2010), and Smith et al. (2016) for surveys.

[2] See Easley et al. (1996, 1997, 2002).

https://doi.org/10.1016/j.jbankfin.2021.106347
0378-4266/

the standard deviations of alphas are adjusted by the Newey and West (1987) procedure (which often produces larger standard deviations than the Politis and Romano's approach), and the Stepwise SPA test by Hsu et al. (2010) is employed to test the return and alpha difference between high- and low-PIN portfolios.

The evidence largely confirms 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. Subtracting the buy-and-hold returns from the MA strategy returns still produces a return difference of 1.116 percent. We perform a time-series regression on the Fama and French (2015) five-factor model with a momentum factor and observe an alpha value of 1.093 percent for return difference. The positive alpha remains significant when the duration of the MA strategy is extended from 10 days to 20 and 50 days and when the portfolio returns are computed using value weighting. We also adopt alternative information asymmetry measures such as Adjusted PIN (Duarte and Young, 2009) and PIN_B/PIN_G (Brennan et al., 2016). While PIN outperforms these measures, the direction remains the same: portfolios subject to high levels of informed trading perform better under the MA strategies.

Next, we conduct a robustness check. We delay the MA trading to the next-day opening, an approach that is yet to be applied in the literature to our knowledge. Traditional research on technical analysis relies on daily data to identify trading signals and to examine the performance of trading strategies. As a result, closing prices have been used to both compute strategy returns and construct trading signals. While it is possible to implement such strategies, orders may not be executed if investors place limit orders. This situation is exacerbated by market orders, wherein trading signals can remain unrealized even after trades have been executed.

To pursue a more realistic implementation of trading strategies, we re-compute the strategy returns on the basis of the next day's opening prices when there are trading signals for the previous days. While such a delay inevitably reduces the profitability of trading strategies, high-PIN portfolios (and those using other information measures) still perform better under the MA strategy than under the buy-and-hold strategy. In addition to examining the outcomes of delaying strategies, we follow Bessembinder and Chan (1998) to estimate breakeven trading costs and the profitability of MA strategies in the sub-sample periods.

Our study suggests that the effectiveness of technical analysis depends on the level of PIN. However, we are not the first one to investigate the relationship between technical analysis and firm characteristics. Shynkevich (2012a) and Shynkevich (2012b) find that technical rules work for small-size firm portfolios; Han et al. (2013) show that high-volatility firms are more profitable by applying MA strategies. Since previous studies, including Aslan, Easley, Hvidkjaer, and O'Hara (2011), find that PIN is cross-sectionally related to several firm characteristics, it is worth exploring if the superior performance of high-PIN portfolios under the MA strategies can be attributed to the correlation between PIN and firm characteristics.

To compare the effects of information measures and other firm characteristics on technical analysis, we adopt a two-dimensional independent sort to categorize the stocks into 16 portfolios. We apply the MA strategies to these portfolios, compare the strategy returns with buy-and-hold returns, and estimate time-series regression alphas. The results reveal that high-PIN portfolios largely outperform low-PIN ones in MA returns and alphas when other characteristics are fixed. However, if the level of PIN is fixed, the expected patterns for difference returns in terms of size, volatility, and liquidity are not observed. The probability of symmetric order-flow shock (PSOS) and analyst forecast dispersion are the only variables that perform as good as or sometimes better than PIN. We, therefore, believe that technical trading rules, particularly the MA strategy, are preferable for securities with high information asymmetry.

Lastly, we examine additional three technical rules, namely, the filter rule, the support and resistance rule, and the channel breakout rule, to see whether information asymmetry affects their performance. The results largely confirm our conjecture. Although these rules do not perform as well as the MA rule, the returns from the low-PIN portfolio still perform much worse than those from the high-PIN portfolio, so that the high-minus-low return differences are positive in most of the strategies. The evidence from alphas are similar except for the mixed result from the channel breakout rule. However, the overall evidence does not suggest that the different performance of technical rules between high- and low-PIN portfolios only takes place in the MA strategy.

The remainder of the article is organized as follows. Section 2 reviews the literature. Section 3 describes the data and the information measures. Section 4 examines the performance of the MA strategy. Section 5 presents robustness checks and findings. Section 6 compares the performance of information measures and other firm characteristics. Section 7 examines alternative technical signals and Section 8 concludes the paper.

2. Review of the literature

2.1. Theories

Proponents of behavioral finance often view the predictability of returns and the effectiveness of technical analysis as evidence supporting the notion that security prices are affected by human errors. Behavioral financial economists offer many arguments to support price continuation or reversal. Daniel et al. (1998) argue that investors are over-confident on their private signals, possibly a result of biased self-attribution, may lead to positive autocorrelation of returns in the short term and negative correlation in the long term. Friesen et al. (2009) develop a model to show that the confirmation bias generates price patterns which predicts returns. Furthermore, investor sentiment may further drives prices away, and with the limits of arbitrage (Shleifer and Vishny, 1997), De Long, Shleifer, Summers, and Waldmann (De Long et al., 1990a; 1990b) argue noisy trader risks will further deter rational traders to correct the price trend. Hong and Stein (1999) demonstrate that boundedly rational newswatchers and momentum traders lead to short-term underreation and long-term overreaction. Conservatism (Barberis et al., 1998) and herding (Bikhchandani et al., 1992) may also contribute to the price trend.

The skeptics of technical analysis are mainly supporters for the efficient market hypothesis. They assert that expected profits cannot be made by extrapolating past prices (Samuelson, 1965; Fama, 1970). A common argument presented in best-selling MBA textbooks such as Bodie et al. (2021) is that the success of technical analysis will likely lead to failure. Investors can easily identify patterns and trade on technical signals, and competition will drive abnormal returns to zero. In the end, security prices are deemed to be unpredictable.

However, at least since 1980s, it has been recognized that return predictability is compatible with efficient markets. The textbook scenario depends on risk-neutral arbitrageurs with abundant leverage capacities, which may not happen in the real world. In a classic consumption-based asset pricing model such as the one in Lucas (1978), the stochastic discount factor depends on the marginal rate of substitution of intertemporal consumption, which is time-varying. As a result, rational investors will not pursue profit-maximization strategies unless they lead to expected utility maximization.[3]

Beginning with Grossman and Stiglitz (1980) and Hellwig (1980), noisy rational expectation models are proposed to show that prices are not fully revealing given that investors are risk averse, that the security supply is random, or that there is an additional sources of risk apart from dividend stream uncertainties. Grundy and McNichols (1989) assume that an exogenous endowment shock prevents price from fully revealing the average private signal. Brown and Jennings (1989) assume dividends and security supply are random. Watanabe (2008) considers an overlapping generation model in which risks come from the risky asset's dividend stream and the random endowments of the asset. In these models, there are more than one sources of uncertainty, and as a result prices are not fully revealing. Combing past and current prices allow investors to estimate security values more accurately than using the current price alone, so technical analysis is valuable to investors. Johnson (2002) develops a model with stochastic dividend growth rate to show the momentum effect without resorting to irrationality or market frictions. Furthermore, Cespa and Vives (2011) derive the conditions under which rational investors engage in momentum and contrarian trading to gain from expectations that are based on historical prices.

How do price series evolve in a market with asymmetric information? Wang (1993) develops a model under which both the dividend and the supply of the security are random. The informed investors know the value of the dividend, and the uninformed only knows its distribution. Because the informed are risk averse, they do not take huge positions to profit from the uninformed. As a result, the current price cannot reveal the two random variables separately, and it partially reveals the trading by the informed. This allows the uninformed to infer the dividend from historical prices. Sometimes they rationally chase the trend and drive up or down the price, and hence there is a sort-term continuation and long-term reversal in price series.

Blume et al. (1994) further explore the usefulness of technical analysis in an information asymmetry environment. They assume that both the means and variances of price signals are random, and as a result, investors' expected utilities increase if they use historical prices and volumes to estimate the asset value. Further, if prior information on security is less precise and market data contain high-quality information, then technical analysis is likely to be effective. They also state that certain securities, such as small-cap or less widely followed stocks, are more affected by private than public information; thus, technical analysis based on private information are more likely to be successful.

2.2. Empirical evidence

While returns can be predictable and technical analysis can be profitable in theory, there is abundant literature empirically investigating the profitability of technical rules. Park and Irwin (2007) and Menkhoff and Taylor (2007) provide comprehensive surveys for applying the rules to various asset classes,[4] and we in this paper only focus on the U.S. equity market in recent decades. Here, different conclusions have been drawn because of different sample periods, methodologies, and asset types. If the sample period excludes this millennium, the profitability of technical analysis is more likely to be supported (Brock et al., 1992; Lo et al., 2000). On the other hand, the evidence support the profitability after year 2000 is weak (Shynkevich, 2012a; 2012b). If the issue multiple hypotheses testing is addressed by using the family of reality checks (White, 2000), the results rarely support the profitability (Sullivan et al., 1999; Marshall et al., 2008b). The superior predictive ability (SPA) tests proposed by Hansen (2005) is more powerful than the reality check, and the researches employing the family of SPA tests may support the profitability more. However, the profitability is still limited to NASDAQ instead of NYSE/AMEX stocks (Hsu and Kuan, 2005), to small instead of technology stocks (Shynkevich, 2012a), and to indices instead of ETFs (Hsu et al., 2010).

Thus, the empirical literature does not offer universal support for the profitability of technical analysis, in contrast to the seemingly popularity in the industry according to surveys. To reconcile the paradox, we speculate that technical rules work better in certain securities, for example, those with high level of information asymmetry. This is the implication of the theoretical models of Wang (1993) and Blume et al. (1994) and has not examined in the empirical literature.

2.3. The moving average rule

The moving average (MA) rule signals buying when the price or the short-term average price moves above the long-term average, and it signals selling when the price or the short-term average moves below the long term average. The rule is among the most successful trading rules studied in the empirical literature.[5] In addition, the applications of MA strategies go beyond the technical analysis literature. Neely et al. (2014) show that technical signals (including MA signals) predict equity premium better than some of the macroeconomic variables. Han et al. (2016) combine MA signals to create a factor to explain short- and long-term reversal and mid-term momentum. Avramov et al. (2021) also combine MA signals to estimate equity returns. Zakamulin and Giner (2020) theoretically show that moving average rules perform better than time-series momentum rules (Moskowitz et al., 2012) given positive autocorrelation in price series, and the empirical evidence is provided by Marshall et al. (2017). Flugum (2021) finds that analyst recommendations levels and changes are often consistent with pervious MA signals, and recommendations that are consistent with previous signals lead to higher subsequent returns than those are not.

Furthermore, theoretical models have been developed in recent years to explain the usefulness of MA signals. Zhu and Zhou (2009) indicate that moving average rules help investor allocate assets and increase expected utilities. Han et al. (2016) modify Wang's (1993) model by replacing the uninformed trader with a technical trader. The price depends on the MA signal if uninformed traders follows MA strategies. Recently, Detzel et al. (2021) provides a general equilibrium model for the MA strategy. They argue that if it is difficult to value the fundamentals of the asset, investors have different priors and rely on the observed price series to move away from their priors. As a result, moving average signals in their model are helpful for investors in pricing the asset.

[3] Cochrane (2011) offers an example. During the bottom of financial crisis, an investor with job uncertainty and asset losses may not want to invest even if stock and bond returns are expected to be remarkably high. The reason is that investing extra money means scarifying current consumption, of which the utility loss was difficult to be compensated at that time.

[4] For more recent contributions in various asset classes, see Marshall et al. (2008a) for commodity futures, Hsu et al. (2016) for currency markets, Shynkevich (2016) for bond markets, and Shynkevich (2017) for Asia-Pacific equity markets.

[5] See Brock et al. (1992), Bessembinder and Chan (1998), and Han et al. (2013). Even among those papers which are not supportive of technical analysis, such as Sullivan et al. (1999) or Marshall et al. (2008b), the majority of their "best" rules are from the MA family.

3. Data and methodology

3.1. Information measures

The main information asymmetry measure used in this study is the probability of informed trading (PIN). We follow Yan and Zhang (2012) to set up the model. Suppose a private information event for a security occurs at the beginning of the day with probability a, and no event occurs with probability $1-a$. The event could announce bad news for the security with probability d or good news with probability $1-d$. In response to news, informed traders may enter the market to buy or sell their securities. In either case, the number of trades by informed traders follows a Poisson distribution with a rate of u. There may also be uninformed trades following Poisson distributions with parameters ϵ_b and ϵ_s denoting purchase and sale, respectively. Fig. 1, Panel A, presents the three scenarios in the model. The likelihood function can be written as a combination of bivariate Poisson distributions:

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

where

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

The set of parameters $\Theta = (a, d, \epsilon_b, \epsilon_s, u)$ in the model is estimated using the order flow information B_t and S_t, which are the number of buy and sell trades at day t. PIN 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 Eq. (3) into PIN resulting from bad and good news:

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

Duarte and Young (2009) extend the PIN model to a more general model and assume that the market witnesses unexpected symmetric order flows with probability l and the arrival rates for buy and sell trades are Δ_b and Δ_s, respectively.[6] Further, the arrival rates of informed buy and sell trades, u_b and u_s, are not necessarily equal. The model, thus, expands the three scenarios in the PIN model into six (see Fig. 1, Panel B). The likelihood function of the adjusted PIN model is written as follows:

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

and

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

where $\Theta^a = (a, d, l, \epsilon_b, u_b, \Delta_b, \epsilon_s, u_s, \Delta_s)$ is the set of model parameters to be estimated. The adjusted probability of informed trading (AdjPIN) is defined as the ratio of expected informed orders to total expected order flow:

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

Duarte and Young (2009) argue that AdjPIN is a more effective information asymmetry measure than PIN. The authors also construct the probability of symmetric order-flow shock as a liquidity measure, which we test in Section 6 of this paper.

Intraday order-flow data are required to estimate the information measures. We collect data from ISSM for the period for 1983–1992 and from TAQ for 1993–2016. Next, we use Lee and Ready's (1991) algorithm to identify buy and sell trades and sum up the daily numbers of trades as B_t and S_t in the above mentioned models. Following Han et al. (2013) and Brennan et al. (2016), we focus on stocks listed on NYSE and AMEX. We adopt Lin and Ke's (2011) factorization approach to estimate the PIN models.

3.2. Trading strategies

We examine daily returns and price data for common stocks from the CRSP, which are marked with a share code 10 or 11 in the database. To achieve reliable PIN estimates and obtain market capitalization data, the PIN portfolios for year n include only those securities that have been traded at least 30 days in year $n-1$ and at the year-end trading day. The stocks are then assigned to decile portfolios on the basis of their PIN values. The portfolios are assumed to be formed at the end of year $n-1$ and held for a year. We begin applying the trading strategies to data since 1984 because the earliest available data on the ISSM are for 1983.

The MA trading strategies used in this paper follow Han et al. (2013). Denote $P_{j,t}$ the closing price for the equally weighted portfolio j at date t. The moving average price with lag L is defined as follows:

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

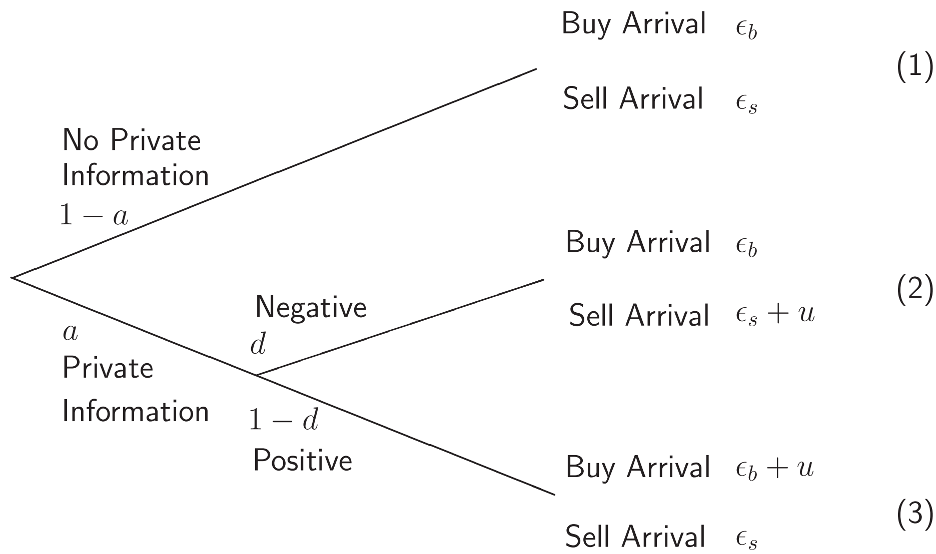
Our trading strategy is to hold the PIN portfolios if their prices are greater than the corresponding MA prices and hold risk-free assets if the prices are lower. This strategy is expected to generate returns during a continuous upward trend and a risk-free rate on a downward trend:

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

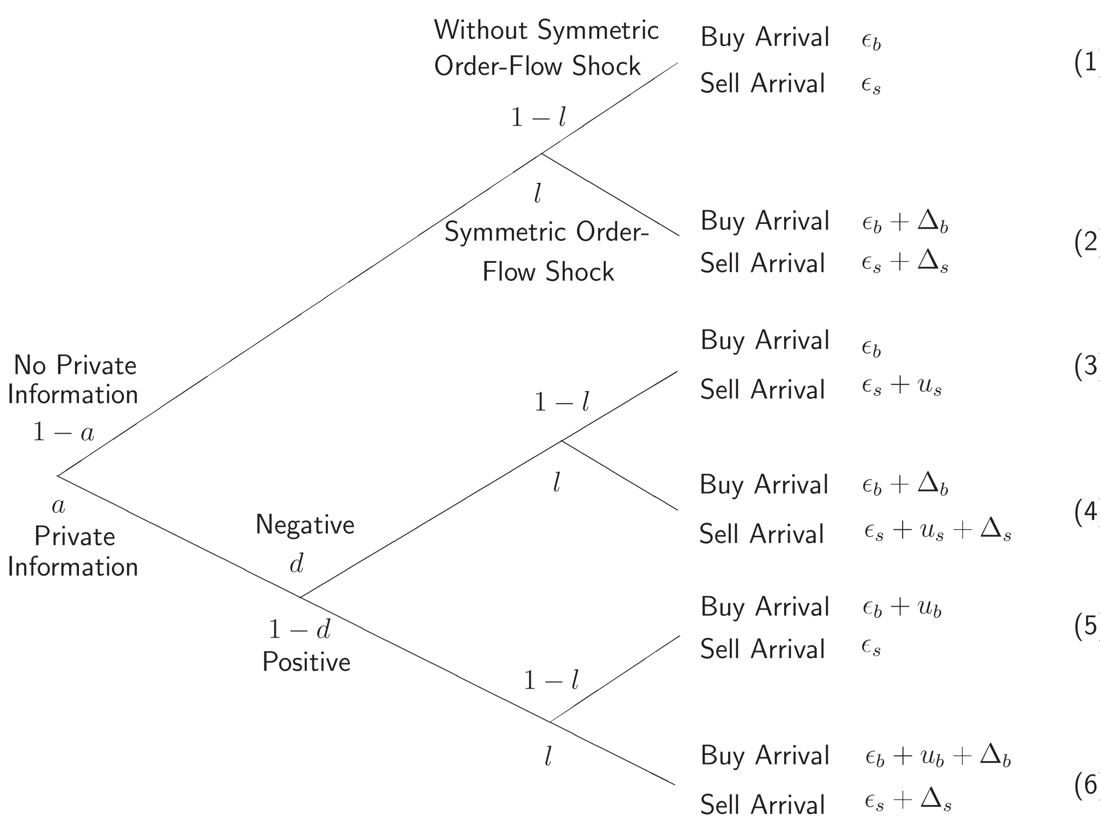
where Rj,t is the daily return for portfolio j on date t, $r_{f,t}$ is the risk-free rate at t, and $\tilde{R}_{j,t,L}$ is the daily return earned using the strategy.[7]

[6] This is Duarte and Young's (2009) Model 4. The authors claim the model to be the best among the others tested in their study.

[7] Since short-selling may involve high transaction costs and sometimes it may be difficult to borrow securities, we do not consider short sales in this paper.



Panel A: The PIN Model



Panel B: The Adjusted PIN Model

Fig. 1. PIN and Adjusted PIN Models.

Table 1
Summary Statistics of PIN Portfolios. The table reports average monthly returns, $R_{j,m}$, the 10-day moving average returns, $\tilde{R}_{j,m,10}$, and their differences, $R^d_{j,m,10}$, for portfolios sorted by PIN in the previous years. It includes mean returns, standard deviations (SD), and t-statistics (in parentheses). *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Sharpe ratios are reported for the portfolio and MA strategy returns. Fractions of the positive difference returns are shown. "H - L" means the return difference between the highest and the lowest PIN deciles.

	PIN Portfolios $R_{j,m}$				MA (10) $\tilde{R}_{j,m,10}$				Difference $R^d_{j,m,10}$			
Decile	Returns		SD	Sharpe	Returns		SD	Sharpe	Returns		SD	+ve
Low	1.389	***	4.51	0.24	1.344	***	3.51	0.30	-0.046		3.05	0.44
	(6.46)				(6.07)				(-0.26)			
2	1.379	***	4.85	0.22	1.485	***	4.02	0.30	0.107		3.57	0.49
	(6.30)				(6.32)				(0.54)			
3	1.316	***	5.20	0.20	1.726	***	4.45	0.32	0.409	*	4.27	0.53
	(5.74)				(6.20)				(1.71)			
4	1.368	***	5.41	0.20	1.862	***	4.82	0.32	0.494		4.44	0.50
	(6.10)				(6.25)				(1.89)			
5	1.401	***	5.49	0.20	2.170	***	4.86	0.38	0.769	*	4.39	0.55
	(5.62)				(6.66)				(2.64)			
6	1.461	***	5.65	0.21	2.257	***	4.82	0.41	0.796	*	4.29	0.53
	(5.58)				(6.66)				(2.77)			
7	1.485	***	5.77	0.21	2.625	***	4.97	0.47	1.140	***	4.23	0.59
	(5.47)				(7.70)				(3.98)			
8	1.672	***	5.93	0.23	2.885	***	4.45	0.58	1.214	***	3.81	0.57
	(5.46)				(8.90)				(4.98)			
9	1.781	***	5.91	0.25	3.226	***	4.23	0.69	1.445	***	3.76	0.63
	(5.77)				(10.72)				(6.49)			
High	2.045	***	5.78	0.30	3.115	***	4.27	0.66	1.070	***	3.44	0.62
	(6.23)				(10.12)				(5.50)			
H - L	0.656	***	4.38	0.40	1.772	***	3.25	0.87	1.116	***	3.21	0.67
	(2.56)				(8.43)				(6.40)			

4. Profitability of technical analysis

4.1. Baseline

Table 1 presents the summary statistics for the MA (10) strategy. We aggregate daily portfolio returns, Rj,t, and daily MA (10) returns, $\tilde{R}_{j,t,10}$, as monthly buy-and-hold returns, $R_{j,m}$ and MA (10) returns, $\tilde{R}_{j,m,10}$. The decile one portfolio, whose average PIN is the lowest, reports an average monthly return of 1.389% under the buy-and-hold strategy and a slightly lower 1.344% when using the MA strategy. PIN increases both portfolio returns (Easley et al., 2002) and MA returns, with the ninth portfolio reporting the highest returns. However, the increase in returns under the MA strategy is significant. Considering the return difference between the highest and lowest decile, the average buy-and-hold return is 0.656%, which is less than the average return of 1.772% under the MA strategy.

Further, the return volatility of the MA strategy, defined as the standard deviation in monthly returns, is considerably lower than that under the buy-and-hold strategy. The MA strategy generates higher Sharpe ratios for all portfolios. We further define return difference, $R^d_{j,m,L}$, as follows:

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

The returns show an increasing trend under PIN, indicating that the MA strategy performs better with high-PIN stocks. The standard deviations of these returns are less than those of buy-and-hold and MA returns. The last column in Table 1 reports the success rate of the strategy, which is defined as the fraction of months when difference returns are positive across the sample period. The ratio is also increasing under PIN and is greater than 60% for the ninth and tenth portfolios, highlighting the consistently greater performance of the MA strategy.

Because of the return distributions may contain fat tails, the traditional t-tests may offer critical values which are so small that too many null hypotheses of no abnormal returns may be falsely rejected. Empirical distributions of t-values may be constructed to overcome this problem.

This paper applies Politis and Romano's (1994) bootstrapping procedure, which has been widely used in the technical analysis literature such as Sullivan et al. (1999), Hsu et al. (2010), and Shynkevich (2012a). Let $\bar{R}_j$ be the mean return of the PIN portfolio j. To test the hypothesis of no significant $\bar{R}_j$, the t-statistics is constructed as

$$\hat{t}(\bar{R}_j) = \frac{\sqrt{M}\bar{R}_j}{\hat{\sigma}_j}, \tag{11}$$

where M is the number of months in the sample, and $\hat{\sigma}_j$ is the sample standard deviation of $R_{j,m}$, for which the sample variance takes the form

$$\begin{aligned} \hat{\sigma}_j^2 &= \hat{R}_j(0) + 2\sum_{m=1}^{M-1} b(m)\hat{R}_j(m), \\ \hat{R}_j(m) &= \frac{1}{M}\sum_{l=1}^{M-m}(R_{j,l} - \bar{R}_j)(R_{j,l+m} - \bar{R}_j), \\ b(m) &= \frac{M-m}{M}0.9^m + \frac{m}{M}0.9^{M-m}. \end{aligned} \tag{12}$$

The t-values of the mean MA (10) portfolios $\bar{R}_{j,m,10}$ and the mean return difference $\bar{R}^d_{j,m,10}$ are computed in the same way and are reported in Table 1. The significant levels of the t-values are obtained from bootstrapping distributions. Take the portfolio return $R_{j,m}$ for example, we perform the following procedure:

1. For each bootstrapping sample $b \in \{1, 2, \ldots, 1000\}$, randomly select a $R_{j,m}$ from the original sample where $m \in \{1, 2, \ldots, M\}$, so that the first observation of the sample is $R_{b^\star,j,1} = R_{j,m}$.
2. The next observation $R_{b^\star,j,2}$ is selected randomly from the original sample with probability 0.1, as in Shynkevich (2012a). With probability 0.9, let $R_{b^\star,j,2} = R_{j,m+1}$. However, if the last observation of the sample $R_{j,M}$ has been chosen in the previous step,

Table 2
Difference Portfolio with Asset Pricing Models. The table reports the results for the time-series regression of monthly difference returns, $R^d_{j,m,10}$, on the Fama and French's (2015) five factor models with a momentum factor in Eq. (13). It presents the coefficients and their t-values (in parentheses). *, **, and *** denote significance at the 0.1, 0.05, and 0.01 levels, 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
	(2.57)		(-10.08)		(0.15)		(-2.82)		(-4.84)		(-1.02)		(0.06)		
2	0.713	**	-0.510	***	-0.053	*	-0.261	***	-0.383	***	-0.130	**	-0.016		0.3414
	(3.14)		(-10.13)		(-0.92)		(-3.03)		(-5.88)		(-1.07)		(-0.32)		
3	1.173	***	-0.606	***	-0.055		-0.469	***	-0.500	***	0.074		-0.096	**	0.3719
	(4.17)		(-9.61)		(-0.65)		(-3.70)		(-6.91)		(0.53)		(-1.69)		
4	1.296	**	-0.613	***	-0.165	***	-0.511	***	-0.531	***	0.078		-0.109	**	0.3687
	(3.71)		(-10.70)		(-2.40)		(-4.24)		(-6.33)		(0.41)		(-1.45)		
5	1.490	***	-0.597	***	-0.195	***	-0.460	***	-0.463	***	0.141		-0.076		0.3488
	(4.29)		(-9.26)		(-2.31)		(-3.31)		(-5.92)		(0.85)		(-1.03)		
6	1.471	***	-0.568	***	-0.299	***	-0.415	***	-0.431	***	0.117		-0.050		0.3479
	(4.59)		(-8.64)		(-3.19)		(-3.15)		(-5.86)		(0.69)		(-0.72)		
7	1.802	***	-0.595	***	-0.245	***	-0.396	***	-0.342	***	0.063		-0.045		0.3675
	(5.99)		(-8.47)		(-3.21)		(-3.34)		(-4.84)		(0.54)		(-0.85)		
8	1.822	***	-0.570	***	-0.398	***	-0.373	***	-0.234	***	0.122	*	-0.077	**	0.4910
	(7.36)		(-12.34)		(-5.71)		(-3.98)		(-3.26)		(1.18)		(-1.90)		
9	1.954	***	-0.539	***	-0.334	***	-0.188	***	-0.193	***	-0.015		0.009		0.4271
	(9.56)		(-8.57)		(-4.98)		(-2.91)		(-2.49)		(-0.15)		(0.16)		
High	1.542	***	-0.430	***	-0.288	***	-0.167	*	-0.294	***	0.000		-0.007		0.3072
	(7.73)		(-8.09)		(-3.89)		(-2.06)		(-3.98)		(0.00)		(-0.15)		
H-L	1.093	***	0.038		-0.294	***	0.016		-0.013		0.081		-0.010		0.0574
	(5.97)		(0.64)		(-4.63)		(0.16)		(-0.13)		(0.54)		(-0.20)		

that is, $m = M$, then we choose the first observation $R_{j,1}$ to be $R_{b^\star,j,2}$.

3. Repeat the previous step until M observations have been chosen. In the end, there are 1000 bootstrapping samples, each of which has M observations.

The empirical distribution for $\hat{t}_j$ is to construct

$$\hat{t}(\bar{R}_{b^\star,j}) = \frac{\sqrt{M}(\bar{R}_{b^\star,j} - \bar{R}_j)}{\hat{\sigma}_j},$$

for distribution b. The significant level of is obtained by sorting the 1000 $\hat{t}(\bar{R}_{b^\star,j})$ in ascending order and compare the t-value $\hat{t}_j$ in Eq. (11) with the 10, 50, 100, 900, 950, and 990-th $\hat{t}(\bar{R}_{b^\star,j})$ to detect the significant level at which the null hypothesis can be rejected. For example, one, two, and three asterisks in Table 1 indicate that the t-values are within 1, 5, and 10% significant levels, respectively.

4.2. Alpha

The monthly return difference, $R^d_{j,m,L}$, is regressed on Fama and French (2015) five-factor asset pricing model plus a momentum factor:

$$R^d_{j,m,10} = \begin{array}{l}\alpha_j + \beta_{j,b}(R_{M,m} - R_{F,m}) + \beta_{j,s}SMB_m + \beta_{j,h}HML_m \\ + \beta_{j,r}RMW_m + \beta_{j,c}CMA_m + \beta_{j,u}UMD_m + \epsilon_m,\end{array} \quad (13)$$

where the returns from the market factor $(R_M - R_F)$, the small-minus-big factor (SMB), the high-minus-low factor (HML), the robust-minus-weak factor (RMW), the conservative-minus-aggressive factor (CMA), and the momentum factor (UMD), are all retrieved from Kenneth French's web site[8].

Table 2 presents the estimated coefficients of the model. The t-statistics are obtained by employing the Newey and West (1987) method to adjust for standard deviations. The significant levels are obtained by comparing the t-statistics with corresponding empirical distributions of α's and β's. The difference portfolios report positive alphas and the high-PIN portfolios show large alphas, with the highest alpha being 1.954% in the ninth decile. The alpha value for the high-minus-low-PIN return difference is 1.093%. Further, all alpha values are larger than the average difference portfolio returns $R^d_{j,m,10}$ (See Table 1), which may be because the factor loadings for $(R_{M,m} - R_{F,m})$, HML, RMW, and most SML are negative. This result is similar to that of Han et al. (2013), who find that the three-factor alphas for their volatility decile portfolios are greater than their returns. This is expected since the difference portfolio, $R^d_{j,m,L}$, is defined by the difference between the MA and buy-and-hold returns. When the MA signal suggests that investors hold a PIN portfolio, the return difference is zero and has zero factor loadings. On the other hand, when the signal is to hold risk-free assets, the return difference is the risk-free rate minus the PIN portfolio return, which tends to have negative factor loadings. When considering both types of signals, the combined return difference tends to have negative loadings.

4.3. MA Length and value-Weighted returns

This section explores different implementations of the MA strategy. We extend the length of day lag L from 10 day to 20 and 50 days. We construct the PIN portfolio using both equally and value-weighted average methods. Table 3 reports the alphas estimated using the six-factor model in Eq. (13). The first column presents the MA (10) strategy results for equally weighted portfolios, which is identical to the original estimated alphas in the first column of Table 2. The second and third columns list the alphas for different portfolios under the MA (20) and MA (50) strategies. All alpha values are positive. Alphas for the high-PIN portfolios tend to be larger than those for the low-PIN ones. The high-minus-low portfolio continues to report significantly positive alphas. However, except for the first portfolio, alphas for longer lags appear to shrink, suggesting that cautious strategies may be less effective in capturing profitable opportunities.

The next three columns in Table 3 report the alphas for different lag strategies applied to value-weighted portfolios. The alpha values further reduce and become negative in the first portfolio. The remaining patterns are similar to those for equally weighted

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

Table 3
Variable Length and Equally vs. Value Weighting Returns for PIN portfolios are computed using either the equally or value - weighted method. The MA strategies are implemented with time lags of 10, 20, and 50 days to estimate the strategy returns. The difference between the strategy returns and portfolio returns, $R^d_{j,m,L}$, is regressed on the six-factor model in Eq. (13). One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

	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	
	(2.57)		(3.02)		(3.99)		(-1.33)		(-0.38)		(-0.43)	
2	0.713	**	0.767	**	0.671	***	0.240		0.164		0.179	**
	(3.14)		(3.19)		(3.33)		(1.27)		(1.00)		(1.19)	
3	1.173	***	1.171	***	0.944	***	0.205		0.293	*	0.298	**
	(4.17)		(4.41)		(3.77)		(0.94)		(1.36)		(1.63)	
4	1.296	**	1.256	***	1.025	**	0.545	**	0.501	*	0.377	*
	(3.71)		(3.91)		(3.27)		(2.40)		(1.94)		(1.61)	
5	1.490	***	1.431	***	1.136	***	0.556	**	0.411	**	0.431	***
	(4.29)		(4.29)		(3.98)		(2.19)		(1.61)		(2.33)	
6	1.471	***	1.497	***	1.249	***	0.660		0.513	*	0.440	*
	(4.59)		(4.98)		(4.47)		(2.38)		(1.87)		(1.85)	
7	1.802	***	1.784	***	1.529	***	0.641		0.589		0.561	**
	(5.99)		(6.79)		(7.13)		(1.96)		(1.79)		(2.03)	
8	1.822	***	1.810	***	1.527	***	0.895	***	0.803	***	0.846	***
	(7.36)		(7.84)		(7.77)		(4.07)		(3.79)		(4.14)	
9	1.954	***	1.857	***	1.560	***	1.310	***	1.275	***	0.948	***
	(9.56)		(8.92)		(6.94)		(5.75)		(7.08)		(4.90)	
High	1.542	***	1.505	***	1.348	***	1.077	***	1.308	***	1.207	***
	(7.73)		(7.01)		(6.42)		(3.24)		(3.72)		(3.59)	
H - L	1.093	***	0.978	***	0.789	***	1.217	***	1.350	***	1.255	***
	(5.97)	###	(5.19)	###	(4.80)	##	(3.89)	##	(4.20)	##	(4.15)	##

portfolios: The MA (50) strategy yields the lowest alphas, high-PIN portfolios report higher alphas, and return difference for the high-minus-low portfolio generate positive alphas. The alphas for the high-PIN portfolios do not fall as much as those for the low-PIN portfolios. The alphas for the high-minus-low portfolios with value-weighted returns are larger than those for equally weighted portfolios.

Although the t-values in this table have passed the 3.0 bar suggested by Harvey et al. (2015) and 3.8 suggested by Chordia et al. (2020), we would like to further address the multiple hypotheses testing problem by implementing the stepwise superior predictive ability (SPA) test proposed by Hsu et al. (2010) to test the null hypothesis that none of the high-minus-low alphas are positive. Let $\hat{t}_k = \sqrt{M}\hat{\alpha}^d_k/\hat{\sigma}^{\alpha d}_k$ be the t-statistics for the k-th high-minus-low alpha, where $\hat{\sigma}^{\alpha d}_k$ is the estimated standard deviation of $\hat{\alpha}^d_k$. To implement the SPA test, we first re-center the test statistics by defining

$$\hat{\mu}_k = \hat{t}_k \cdot 1(\sqrt{M}\hat{\alpha}^d_k \le -\hat{\sigma}^{\alpha d}_k\sqrt{2\log\log M}),$$

where $1(X)$ is the indicator function which takes the value one when the condition X is true and zero otherwise. Let $t_{b^\star_k}$ be the t-values of k-th alpha obtained from the $b^\star$ distribution. The critical value at p% significant level is the $(100-p)$-th percentile of the distribution of

$$\max_k\{\max(t_{b^\star_k} + \hat{\mu}_k, 0)\}. \tag{14}$$

The null hypothesis of zero high-minus-low portfolio return for strategy k is rejected if its t-value $\hat{t}_k$ is greater than the critical value.

If none of the null hypothesis $\bar{\alpha}^d_k = 0$ is rejected, then the Stepwise SPA tests stop here. If some of $\bar{\alpha}^d_k$ is significantly greater than zero, then we remove those sample and perform another SPA test on the rest of the data. We keep performing this procedure until none of the remaining $\bar{\alpha}^d_k$ can be rejected.

Because the quantiles of the SPA test in (14) take the maximum t values of all models of interest, the critical values are much larger than the ones using in a single-model test. The bottom row of Table 3 report the test result under the null hypothesis that none of the high-minus-low alphas in this table is significantly greater than zero, where one, two and three hashes (#) indicate that the t-values are significant at 10, 5, and 1% level, respectively. Under the new critical values, all of the high-minus-low returns remain significant at five percent level.

Given the evident difference between the results for equally and value-weighted portfolios, the effectiveness of the MA strategies may differ between large and small firms, and we will return to this issue in Section 6.1.

4.4. Alternative measures

Table 4 reports the portfolio return difference, $R^d_{j,m,L}$, and their six-factor alphas for the alternative information measures, PIN_B, PIN_G, and Adjusted PIN. We construct equally weighted portfolios with the MA (10) strategy. Here as well, portfolios with higher PIN_B, PIN_G, and Adjusted PIN values tend to have greater return difference and alphas. On the other hand, the spread of returns and alphas for the high-minus-low portfolios are smaller than those for the PIN portfolios. The portfolios constructed on the basis of PIN_G behave more like those based on PIN, in that their high-minus-low difference returns $R^d_{j,m,L}$ and alpha pass the Stepwise SPA tests.[9]

[9] The null hypothesis of the Stepwise SPA test for $R^d_{j,m,L}$ is that difference returns for MA (10) strategy are all zero for the high-minus-low PIN, PIN_B, PIN_G, and Adjusted PIN portfolios. Similarly, the null hypothesis for alphas is that they are all zero for these strategies.

Table 4
Alternative Measures. The table reports the difference returns for the MA (10) strategy, $R^d_{j,m,10}$, and their alphas from the six-factor model in Eq. (13) for equally weighted portfolios sorted on the basis of PIN_B, PIN_G, and Adjusted PIN. It presents the mean differences, alphas, and their t-values (in parentheses) are reported. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

	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	***
	(2.63)		(4.89)		(1.69)		(3.81)		(2.18)		(4.85)	
2	0.453		1.101	**	0.241		0.840	***	0.289		0.869	**
	(1.89)		(4.07)		(1.15)		(3.77)		(1.35)		(3.80)	
3	0.620	**	1.300	***	0.275		0.916	***	0.291		0.970	**
	(2.62)		(4.68)		(1.20)		(3.79)		(1.24)		(3.59)	
4	0.558	*	1.235	***	0.516	*	1.182	***	0.548		1.303	**
	(2.56)		(4.69)		(2.20)		(4.31)		(2.05)		(3.87)	
5	0.545	*	1.230	***	0.595	*	1.256	***	0.726	**	1.436	***
	(2.17)		(4.43)		(2.45)		(4.46)		(2.65)		(4.38)	
6	0.763	***	1.444	***	0.719	*	1.348	***	0.925	**	1.603	***
	(3.37)		(5.98)		(2.75)		(4.63)		(3.20)		(5.07)	
7	0.840	***	1.414	***	0.962	***	1.604	***	0.848	***	1.543	***
	(3.72)		(5.96)		(4.12)		(6.29)		(3.36)		(5.66)	
8	1.135	***	1.666	***	0.955	***	1.582	***	1.095	***	1.718	***
	(4.54)		(6.84)		(4.39)		(6.95)		(3.95)		(6.39)	
9	1.008	***	1.548	***	1.237	***	1.865	***	1.170	***	1.660	***
	(4.50)		(7.37)		(4.76)		(7.09)		(5.49)		(8.28)	
High	0.944	***	1.507	***	1.285	***	1.823	***	0.906	***	1.306	***
	(3.80)		(5.65)		(5.33)		(8.15)		(4.95)		(7.23)	
H - L	0.401	*	0.287		0.915	***	0.812	***	0.451	***	0.220	
	(1.69)	#	(1.02)		(3.78)	#	(3.31)	#	(2.49)	#	(1.09)	

5. Robustness checks

5.1. Next-Day trading

Research examining technical signals and strategies often relies on daily data comprising closing trade prices and the averages of closing bid and ask prices. Closing prices are also used to detect signals and study the outcomes of implemented strategies. For example, our strategy applies the closing price for date t, $P_{j,t}$, to compute signal $A_{j,t,L}$ in Eq. (8) and implement the trading strategy in Eq. (9). While not impossible, executing this approach can be difficult, particularly when there is high uncertainty regarding whether a trading condition can be met. For instance, if an investor submits a limit order, the order might not be executed even though the MA condition is met. On the other hand, a market order might be executed even if the condition is 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 uncertain. If there is a buy signal on $t-1$, then we buy securities at the opening of t. Likewise, if there is a sell signal, we sell the securities at the next opening. We use closing prices to construct trading signals. Define $P^o_{j,t}$ the opening price at t, and $P_{j,t}$ remains the closing price. We define open-to-close, close-to-open, and close-to-close returns for portfolio j as follows:

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

Note that the definitions can be modified to allow for cash dividends and stock splits. The return at time t are contingent on both the trading signal at $t-1$ and the portfolio holding on the day. Suppose risk-free assets are held at $t-1$, then the next-day return is $r_{f,t}$ if the investor continues to hold the assets, or it is $R^{oc}_{j,t}$ if the trading signal suggests switching to a PIN portfolio. Now suppose that the investors hold a PIN portfolio at $t-1$, then the next-day return is Rj,t if they continue to hold the portfolio, or $(1+R^{co})(1+r_{f,t})-1$ if they sell the portfolio to buy risk-free assets on day t. Therefore, the MA return from Eq. (9) can be rewritten as follows:

$$\tilde{R}_{j,t,L} = \begin{cases} Rj,t, & \text{if the } j\text{-th portfolio are held at } t-1 \text{ and } P_{j,t-1} > A_{j,t-1,L}; \\ (1+R^{co})(1+r_{f,t})-1 & \text{if the } j\text{-th portfolio are held at } t-1 \text{ and } P_{j,t-1} \le A_{j,t-1,L}; \\ R^{oc}_{j,t} & \text{if risk-free assets are held at } t-1 \text{ and } P_{j,t-1} > A_{j,t-1,L}; \\ r_{f,t} & \text{if risk-free assets are held at } t-1 \text{ and } P_{j,t-1} \le A_{j,t-1,L}; \end{cases} \tag{15}$$

where available, we use opening trade prices from TAQ and ISSM to compute Eq. (15); otherwise, we use the average opening bid and ask prices. If neither is available, we replace $P^o_{j,t}$ with closing price $P_{j,t}$.

Table 5 reports the return difference, $R^d_{j,t,L}$, and its six-factor alpha for the strategies implemented at the next-day openings. Panel A presents the results for the MA (10) strategy. Delaying trades to the next opening severely erodes profits. Most of the returns and alphas show a one-third decrease, and positive difference returns appear only in portfolios with high levels of information trading. On the other hand, the modified strategy does not significantly affect the high-minus-low portfolios and the changes in returns and alphas are much smaller and sometimes positive. This can be attributed to the substantial declines in the returns and alphas of the first decile portfolios. We further perform Stepwise SPA tests on the high-minus-low difference returns and alphas.[10] Both PIN and PIN_G pass the tests, and the return difference of PIN_B portfolio is also significant at 10% level.

Panel B in Table 5 reports the results for the MA (50) strategy. We observe a further drop only in the decile 9 and 10 portfolios with PIN and PIN_G and the return difference and alphas of high-

[10] The null hypotheses are none of the high-minus-low difference returns (or alphas) the in the two panels of this table are significant.

Table 5
Trade at the Next Opening. The table reports the results for the MA (10) and MA (50) strategies implemented at the opening of day t by observing the signal at the closing of $t-1$. The portfolios are sorted by PIN, PIN_B, PIN_G, and the Adjusted PIN. It presents the difference returns, $R^d_{j,m,L}$, their alphas for the six-factor model, and t-values (in parentheses). One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

Panel A: Results for MA (10) Strategy

	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	***
	(-2.29)		(0.22)		(0.32)		(2.86)		(-1.38)		(0.92)		(0.13)		(2.49)	
2	-0.162		0.261	*	0.029		0.484	***	-0.009		0.463	***	-0.132		0.311	**
	(-0.95)		(1.45)		(0.15)		(2.34)		(-0.04)		(2.32)		(-0.71)		(1.60)	
3	0.044		0.554	***	0.231	*	0.715	***	-0.098		0.406	**	0.052		0.503	**
	(0.22)		(2.82)		(1.11)		(3.36)		(-0.55)		(2.18)		(0.24)		(2.11)	
4	0.279		0.768	***	0.321	**	0.794	***	0.218		0.694	***	-0.020		0.485	**
	(0.96)		(2.42)		(1.27)		(2.97)		(0.83)		(2.44)		(-0.10)		(2.19)	
5	0.164		0.648	**	0.112		0.628	***	0.144		0.621	**	0.223		0.695	***
	(0.80)		(2.95)		(0.60)		(3.62)		(0.75)		(3.01)		(0.96)		(2.80)	
6	0.165		0.627	***	0.164	*	0.629	***	0.207		0.640	***	0.265		0.722	**
	(0.81)		(3.12)		(0.93)		(3.74)		(1.06)		(3.16)		(1.30)		(3.48)	
7	0.294	*	0.708	***	0.229	**	0.670	***	0.347	***	0.822	***	0.167		0.600	***
	(1.51)		(3.60)		(1.31)		(3.94)		(1.83)		(4.48)		(0.95)		(3.53)	
8	0.360	**	0.808	***	0.302	**	0.743	***	0.280	**	0.739	***	0.350	**	0.779	***
	(1.79)		(4.31)		(1.64)		(3.87)		(1.45)		(4.16)		(1.66)		(3.72)	
9	0.689	***	1.131	***	0.378	***	0.755	***	0.442	***	0.865	***	0.582	***	0.989	***
	(3.73)		(6.58)		(2.16)		(4.57)		(2.20)		(4.32)		(3.38)		(6.46)	
High	0.563	***	0.870	***	0.444	***	0.819	***	0.717	***	1.045	***	0.414	***	0.772	***
	(3.93)		(6.26)		(2.94)		(4.63)		(4.12)		(7.16)		(3.15)		(6.40)	
H - L	0.923	***	0.834	***	0.392	***	0.326	***	0.920	***	0.901	***	0.388	***	0.293	**
	(5.89)	###	(4.81)	###	(3.31)	#	(2.51)		(6.70)	###	(6.22)	###	(2.37)		(1.70)	

Panel B: Results for MA (50) Strategy

	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	***
	(-1.18)		(1.88)		(-0.75)		(2.37)		(-1.37)		(1.86)		(-1.17)		(2.47)	
2	-0.112	*	0.320	***	-0.112		0.372	***	-0.074		0.351	***	-0.198	**	0.288	***
	(-0.90)		(2.66)		(-0.78)		(2.43)		(-0.49)		(2.58)		(-1.47)		(1.98)	
3	-0.091		0.397	***	-0.029		0.459	***	-0.089		0.372	***	-0.068		0.390	***
	(-0.57)		(2.46)		(-0.19)		(3.29)		(-0.63)		(2.75)		(-0.49)		(2.46)	
4	-0.054		0.422	**	0.115		0.638	***	0.005		0.487	***	-0.066		0.420	**
	(-0.30)		(1.94)		(0.70)		(3.59)		(0.03)		(2.58)		(-0.38)		(2.09)	
5	-0.053		0.434	***	0.010		0.523	***	-0.054		0.418	***	0.026		0.514	***
	(-0.35)		(3.00)		(0.06)		(3.68)		(-0.41)		(3.16)		(0.15)		(2.62)	
6	-0.047		0.413	***	-0.023		0.436	***	0.021		0.466	***	-0.004		0.469	***
	(-0.30)		(2.54)		(-0.15)		(3.31)		(0.15)		(3.09)		(-0.02)		(2.92)	
7	0.081		0.547	***	0.076		0.506	***	0.030		0.507	***	0.019		0.482	***
	(0.53)		(3.86)		(0.50)		(4.23)		(0.19)		(3.39)		(0.12)		(3.24)	
8	0.121		0.601	***	0.098	*	0.526	***	0.125		0.615	***	0.199	*	0.667	***
	(0.75)		(4.36)		(0.73)		(4.66)		(0.85)		(4.73)		(1.15)		(4.97)	
9	0.321	***	0.761	***	-0.002		0.387	***	0.182	**	0.616	***	0.262	***	0.683	***
	(2.20)		(5.60)		(-0.01)		(3.41)		(1.39)		(5.05)		(1.74)		(5.08)	
High	0.278	***	0.648	***	0.035		0.414	***	0.420	***	0.836	***	0.093	**	0.407	***
	(2.25)		(4.61)		(0.31)		(2.71)		(2.91)		(6.44)		(0.90)		(3.05)	
H - L	0.427	***	0.441	***	0.146		0.030		0.577	***	0.608	***	0.263	***	0.120	
	(4.59)	###	(3.94)	##	(1.31)		(0.27)		(5.04)	###	(4.71)	##	(2.43)		(1.01)	

minus-small portfolios, but those difference returns and alpha remain significant.

5.2. Trading and costs

Table 6 presents the average annual holding days (Holding), average annual trading (Trading), and breakeven trading costs (BETC) following Bessembinder and Chan (1998) for the MA strategies applied to portfolios sorted using four information asymmetry measures. The number of holding days ranges between 220 and 240 for the MA (10) strategy and between 240 and 260 for the M(50) strategy. The number of trading times range from 30 to 40 for the MA (10) strategy and from 9 to 16 for the MA (50) strategy. Since the change in the 50-day moving average is relatively small, trading is less frequently triggered, and the holding days for the portfolios are greater under this strategy than the MA (10) strategy. Within the same strategy, the differences in holding days and trading times among all information measure portfolios are small. Portfolios with high information asymmetry report less trading. Therefore, breakeven trading costs, defined as the annual returns of the MA (L) strategy $\tilde{R}_{j,n,L}$ divided by trading times, are high when information asymmetry is severe. Under the MA (50) strategy, the breakeven trading costs are greater than four percent, much larger than the costs of the MA (10) strategy.

The table also reports the “SPA indifferent” transaction costs. They are the lowest costs under which the null hypothesis that none of the return difference $R^d_{j,m,L} = \tilde{R}_{j,m,L} - R_{j,m}$ of the decile portfolios of the information measure are positive cannot be rejected at the 10% significant level. This is a much stricter test than

Table 6
Trading, Holding, and Costs. The tables report the average holding days (Holding), the annual number of trades, and the breakeven trading costs of the MA (10) and MA (50) strategies for the portfolios formed as per 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: Results for MA (10) Strategy												
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
SPA Indifferent			0.330			0.160			0.243			0.213
Panel B: Results for MA (50) Strategy												
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
SPA Indifferent			0.575			0.325			0.590			0.500

evaluating break-even points. Firstly, this test essentially compares the MA return with the buy-and-hold return, whereas BETC only considers whether the trading strategies earn positive profits. Secondly, it is not enough for the return difference to be positive; the return difference has to be large enough to be at the borderline of 10% level. Thirdly, the SPA test statistics in Eq. (14) considers the maximum quantile of all bootstrapping distributions, which further increases the critical value. As a result, the SPA indifferent costs are much lower than the BETC. The literature often uses 0.5% as the estimated round-trip costs (Novy-Marx and Velikov, 2016), and other estimates range from 0.26% (Ready, 2002), 0.49% (Keim and Madhavan, 1997) to 1.5% (Grundy and Martin, 2001). The estimated one-way SPA indifferent costs of PIN_B, PIN_G and Adjusted PIN for the MA (10) strategy are below the estimates in the literature.

From the traditional view of efficient market hypothesis in 1960s or 1970s, if the profits earned by technical analysis exceed the costs, then the market is not weak-form efficient, and rational investors should take the profits away. However, more recent studies such as Brown and Jennings (1989) and Wang (1993) have shown that it does not increase the expected utility of risk-averse informed investors to trade aggressively. The seemingly net profits of the PIN portfolios shown here, therefore, are consistent with noisy rational expectation models.[11]

5.3. Profitability over time

Research has suggested that the market is getting more "efficient" in recent years (Bai et al., 2016), and technical analysis may be losing its charm. Shynkevich (2012a), for example, states that technical rules are ineffective in the case of small stocks in the second half of their sample period (11/29/02 to 6/30/10). Table 7 presents some evidence echoing these claims. We divide the sample into three sub-periods: 1984–1995, 1996–2006, and 2007–2017. We apply the MA (10) strategy to portfolios sorted by the information measures in the sub-periods. The strategy indeed performs better in the early periods than the 2007–2017 period. All portfolio difference returns and alphas are positively significant in the early periods, and some of them become negative in the last period. For the portfolio with high levels of information asymmetry, however, $R^d_{j,m,10}$ is often the highest in the second sub-period and remains positive in the third period such that all high-minus-low returns of all information measures are significant in the last period. Furthermore, all the high-minus-low difference returns for the PIN portfolios pass the SPA test for both $R^d_{j,m,10}$ and alphas.[12] The high-minus-low PIN_G portfolio also passes some of the SPA test in the later periods. The results imply that the MA strategy is profitable for portfolios with a high degree of information asymmetry throughout the sample period despite the decline in profits.

6. Other variables

Aslan et al. (2011) relate PIN with various firm characteristics, highlighting the possibility that other factors can better identify profitable portfolios under MA strategies. Therefore, we compare the performance of information measures with a series of variables using 4 × 4 independently sorted portfolios. For each set of 16 portfolios, we follow the procedure similar to that in the previous sections to calculate portfolio difference returns and six-factor alphas.[13]

[11] Furthermore, for those who view the tests of trading rules as tests for market efficiency, the technique "must have been in use in a substantial part of the sample period (Sullivan et al., 1999, p.1655)." Our study does not fit this criteria. Although PIN was developed in the mid-1990s, the trading volumes grow so much that its estimation soon ran into difficulties in early 2000s. The estimation problem was not solved until Lin and Ke (2011) propose a new algorithm. It means that investors are unlikely to compute PIN in a substantial part of our sample period.

[12] The null hypotheses of the SPA tests are none of the high-minus-low portfolios (or alphas) are positively significant for any information measures in any sub-periods.

[13] As PIN and a few variables are highly correlated, independent five-by-five or even more sorts would leave too many missing groups in some years. This is not to say there are no missing four-by-four groups. Between the sample period 1983 to 2017,there is one group missing in one year for Illiq-PIN sort and Cover-PIN sort,

Table 7
Profitability Over Sample Period. The table reports the profitability of the MA (10) strategy in the sub-sample periods of 1984–1995, 1996–2006 and 2007–2017, for the portfolios formed by PIN, PIN_B, PIN_G, and adjusted PIN. It reports the difference returns, $R^d_{j,m,L}$, their alphas for the six-factor model, and t-values (in parentheses). One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

	PIN						PIN_B					
	1984–1995		1996–2006		2007–2017		1984–1995		1996–2006		2007–2017	
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	$R^d_{j,m,10}$	α_j	$R^d_{j,m,10}$	α_j
Low	0.455 ***	0.871 ***	-0.005	0.559 ***	-0.633 *	-0.176	1.098 ***	1.690 ***	0.783 ***	1.632 ***	-0.303 **	0.140
	(2.90)	(5.26)	(-0.01)	(1.90)	(-1.91)	(-0.75)	(6.11)	(14.50)	(2.24)	(4.13)	(-0.93)	(0.53)
2	0.569 ***	1.123 ***	0.334 *	1.181 ***	-0.625 ***	-0.231 **	0.903 ***	1.510 ***	0.991 ***	1.783 ***	-0.578 ***	-0.077
	(2.73)	(6.79)	(0.89)	(3.27)	(-2.30)	(-1.42)	(4.14)	(7.14)	(2.36)	(4.33)	(-1.75)	(-0.30)
3	0.967 ***	1.572 ***	0.688 **	1.761 ***	-0.477 *	-0.013	0.939 ***	1.585 ***	1.201 ***	2.050 ***	-0.308	0.124 *
	(5.03)	(10.03)	(1.48)	(3.67)	(-1.30)	(-0.05)	(4.07)	(9.00)	(2.97)	(4.47)	(-0.80)	(0.54)
4	0.911 ***	1.444 ***	1.230 ***	2.516 ***	-0.698 ***	-0.261	1.031 ***	1.588 ***	1.016 ***	1.935 ***	-0.415 *	0.149
	(4.08)	(7.54)	(2.77)	(4.95)	(-2.19)	(-0.84)	(5.02)	(11.25)	(3.19)	(4.88)	(-1.19)	(0.53)
5	1.219 ***	1.779 ***	1.592 ***	2.632 ***	-0.546 *	-0.061	1.037 ***	1.586 ***	1.137 ***	2.052 ***	-0.583 **	-0.075
	(4.99)	(9.49)	(3.41)	(5.06)	(-1.29)	(-0.18)	(4.48)	(8.04)	(3.02)	(5.71)	(-1.52)	(-0.24)
6	1.242 ***	1.887 ***	1.551 ***	2.287 ***	-0.444	0.138	1.051 ***	1.589 ***	1.225 ***	2.103 ***	-0.013	0.566 ***
	(4.90)	(9.75)	(3.73)	(4.39)	(-0.94)	(0.35)	(4.22)	(7.24)	(3.04)	(5.21)	(-0.03)	(2.20)
7	1.479 ***	1.965 ***	1.624 ***	2.350 ***	0.288	0.908 ***	1.149 ***	1.549 ***	1.255 ***	2.028 ***	0.089	0.494 ***
	(6.59)	(9.89)	(4.03)	(6.00)	(0.44)	(1.58)	(5.12)	(8.66)	(3.61)	(5.33)	(0.20)	(1.51)
8	1.118 ***	1.615 ***	1.812 ***	2.486 ***	0.720 ***	1.184 ***	1.519 ***	2.098 ***	1.667 ***	2.210 ***	0.184	0.677 ***
	(5.10)	(9.16)	(3.73)	(4.99)	(1.64)	(3.34)	(5.34)	(9.44)	(4.23)	(5.58)	(0.47)	(2.79)
9	1.635 ***	2.203 ***	1.467 ***	1.865 ***	1.215 ***	1.607 ***	1.108 ***	1.720 ***	1.310 ***	1.837 ***	0.598 ***	1.050 ***
	(5.73)	(9.55)	(3.46)	(4.32)	(2.88)	(5.80)	(3.37)	(6.77)	(3.45)	(4.53)	(1.46)	(3.89)
High	1.139 ***	1.735 ***	1.339 ***	1.879 ***	0.726 ***	0.970 ***	0.891 ***	1.407 ***	1.097 **	1.708 ***	0.848 ***	1.114 ***
	(4.35)	(9.38)	(3.40)	(5.75)	(2.55)	(4.21)	(2.47)	(3.23)	(2.12)	(3.65)	(2.26)	(3.48)
H - L	0.684 ***	0.864 ***	1.344 ***	1.320 ***	1.359 ***	1.146 ***	-0.207	-0.283	0.314	0.076	1.151 ***	0.975 ***
	(3.05) ##	(5.25) ###	(4.11) ###	(3.57) ##	(4.86) ###	(3.35) #	(-0.56)	(-0.66)	(0.77)	(0.22)	(4.27) ###	(2.94)

	PIN_G						Adjusted PIN					
	1984–1995		1996–2006		2007–2017		1984–1995		1996–2006		2007–2017	
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	$R^d_{j,m,10}$	α_j	$R^d_{j,m,10}$	α_j
Low	0.822 ***	1.206 ***	0.467 **	1.402 ***	-0.220	0.241 *	0.963 ***	1.396 ***	0.675 ***	1.421 ***	-0.317	0.242 **
	(2.45)	(3.05)	(1.31)	(3.41)	(-0.59)	(0.83)	(4.26)	(8.34)	(2.30)	(3.85)	(-0.81)	(0.86)
2	0.830 ***	1.369 ***	0.385 **	1.133 ***	-0.544 *	-0.072	1.008 ***	1.627 ***	0.331 *	0.962 ***	-0.538	-0.044
	(4.45)	(8.41)	(1.21)	(3.00)	(-1.41)	(-0.30)	(5.23)	(10.72)	(1.06)	(2.74)	(-1.46)	(-0.16)
3	0.896 ***	1.556 ***	0.411 **	1.100 ***	-0.537 *	-0.056	1.068 ***	1.672 ***	0.380 *	1.348 ***	-0.646 ***	-0.253
	(4.64)	(11.43)	(1.15)	(2.84)	(-1.31)	(-0.18)	(5.18)	(8.77)	(0.94)	(3.47)	(-1.95)	(-0.99)
4	0.945 ***	1.518 ***	0.873 ***	1.845 ***	-0.309	0.134	1.100 ***	1.663 ***	1.128 ***	2.209 ***	-0.632 ***	-0.263 *
	(4.55)	(8.97)	(2.20)	(4.16)	(-0.71)	(0.34)	(4.17)	(10.03)	(2.42)	(4.03)	(-1.92)	(-1.14)
5	1.103 ***	1.605 ***	1.128 ***	1.914 ***	-0.493 *	-0.019	1.103 ***	1.729 ***	1.409 ***	2.377 ***	-0.368 *	0.064
	(4.82)	(8.89)	(2.87)	(4.68)	(-1.42)	(-0.07)	(5.01)	(9.31)	(2.86)	(4.30)	(-0.89)	(0.18)
6	1.117 ***	1.744 ***	1.367 ***	2.193 ***	-0.362	0.021	1.233 ***	1.845 ***	1.787 ***	2.685 ***	-0.272	0.237
	(4.71)	(9.23)	(3.52)	(5.03)	(-0.82)	(0.06)	(5.48)	(8.48)	(4.43)	(6.45)	(-0.53)	(0.57)
7	1.094 ***	1.646 ***	1.750 ***	2.556 ***	0.030	0.478 ***	0.902 ***	1.443 ***	1.598 ***	2.393 ***	0.038	0.633 ***
	(4.42)	(8.74)	(4.81)	(7.28)	(0.08)	(2.50)	(4.17)	(7.14)	(3.46)	(4.97)	(0.09)	(1.88)
8	1.181 ***	1.741 ***	1.336 ***	2.087 ***	0.328 *	0.805 ***	1.063 ***	1.546 ***	1.846 ***	2.482 ***	0.380	0.967 ***
	(5.22)	(11.43)	(3.18)	(4.77)	(0.87)	(2.51)	(5.32)	(8.20)	(4.12)	(5.75)	(0.64)	(2.31)
9	1.434 ***	2.025 ***	1.763 ***	2.449 ***	0.495 **	1.002 ***	1.025 ***	1.584 ***	1.373 ***	1.836 ***	1.125 ***	1.487 ***
	(5.09)	(9.35)	(3.70)	(5.40)	(1.07)	(3.06)	(3.58)	(6.09)	(2.89)	(3.93)	(3.55)	(8.80)
High	1.151 ***	1.666 ***	1.796 ***	2.312 ***	0.922 ***	1.254 ***	1.056 ***	1.539 ***	0.924 ***	1.279 ***	0.725 ***	1.025 ***
	(4.41)	(11.89)	(3.26)	(4.70)	(2.85)	(6.16)	(3.81)	(4.93)	(2.74)	(4.09)	(2.46)	(4.99)
H - L	0.329	0.460	1.328 ***	0.910 ***	1.142 ***	1.013 ***	0.093	0.143	0.249	-0.142	1.042 ***	0.783 ***
	(0.75)	(1.06)	(2.85) ##	(2.26)	(5.37) ###	(4.37) ##	(0.33)	(0.44)	(1.03)	(-0.57)	(3.54) ##	(2.35)

Table 8 reports the descriptive statistics for the characteristics and information measures. Panel A shows the average annual cross-sectional means and standard deviations, and Panel B lists the average annual Pearson and Spearman correlation coefficients in the upper-right and bottom-left of the matrix, respectively. We briefly discuss the statistics for firm characteristics here and delve deeper in computation details in the subsequent sections. First, the mean value for PIN, which is the sum of PIN_B and PIN_G, is 0.185. This value is considerably smaller than the sum of the mean values for Adjusted PIN and PSOS (0.405). Second, PIN is positively correlated with PIN_B, PIN_G, Adjusted PIN, and even PSOS. Third, the market value of equity (MV) and the number of analysts covering the firm (Cover) are positively correlated, and the two variables are negatively correlated with the other variables except for Pástor and Stambaugh's gamma, which reports a small correlation. Finally, the other liquidity variables including quoted spread, Amihud 's (2002) illiquidity measure, and PSOS are positively correlated with each other and the information measures. The only exception is the small correlation between adjusted PIN and PSOS. In other words, it is difficult to disentangle information asymmetry from other liquidity sources.

two groups missing in one year for the Qsp-PIN sort, and one group missing in two years for the MV-PIN sort. These years' samples are removed from the analysis. There is no missing group of PIN intersected with STD, IVOL, Gamma, PSOS, or Disp.

Table 8

Descriptive Statistics for Information Measures and Firm Characteristics. The tables report the average annual statistics for the information measures, PIN, PIN_B, PIN_G, and Adjusted PIN (AdjPIN) and firm characteristics including the market value of equity (MV; in billion dollars), the standard deviations of daily returns (STD) and quarterly operating incomes scaled by total assets (IVOL), quoted spread (QSP), Amihud's (2002) illiquidity measure (Illiq), Pástor and Stambaugh's (2003) illiquidity measure (Gamma), Duarte and Young's (2009) probability of symmetric order-flow shocks (PSOS), number of analysts covering the firm (Cover), and earnings forecasts' dispersion (Disp). Panel A reports the time-series averages of the cross-sectional means and standard deviations of the variables. Panel B presents the averages of the cross-sectional Pearson (upper-right half) and Spearman (bottom-left half) correlation coefficients.

Panel A: Averages of Cross-Sectional Statistics

	PIN	PIN_B	PIN_G	AdjPIN	MV	STD	IVOL	Qsp	Illiq	Gamma	PSOS	Cover	Disp
Mean	0.185	0.077	0.108	0.150	4.1	0.027	0.056	0.020	0.007	-0.002	0.255	6.555	0.033
Std	0.085	0.076	0.060	0.071	14.2	0.026	1.199	0.048	0.063	0.151	0.133	7.940	0.751

Panel B: Correlation Coefficients

	PIN	PIN_B	PIN_G	AdjPIN	MV	STD	IVOL	Qsp	Illiq	Gamma	PSOS	Cover	Disp
PIN		0.730	0.488	0.510	-0.206	0.278	0.078	0.363	0.153	-0.008	0.342	-0.430	0.058
PIN_B	0.509		-0.230	0.300	-0.096	0.141	0.031	0.224	0.116	-0.011	0.200	-0.218	0.029
PIN_G	0.603	-0.230		0.359	-0.174	0.222	0.073	0.244	0.077	0.003	0.231	-0.347	0.038
AdjPIN	0.582	0.391	0.380		-0.206	0.199	0.052	0.367	0.160	-0.016	-0.031	-0.420	0.053
MV	-0.587	-0.340	-0.400	-0.542		-0.130	-0.049	-0.130	-0.038	0.002	-0.116	0.478	-0.028
STD	0.336	0.098	0.274	0.239	-0.423		0.156	0.550	0.417	-0.017	0.185	-0.200	0.191
IVOL	0.212	0.088	0.162	0.165	-0.348	0.354		0.135	0.066	-0.006	0.064	-0.108	0.057
Qsp	0.583	0.332	0.400	0.536	-0.893	0.505	0.332		0.568	-0.037	0.138	-0.324	0.216
Illiq	0.614	0.364	0.412	0.569	-0.959	0.516	0.345	0.939		0.009	0.074	-0.129	0.110
Gamma	-0.012	-0.007	-0.006	-0.010	0.017	-0.001	-0.011	-0.015	-0.018		0.006	0.008	0.009
PSOS	0.501	0.187	0.337	0.109	-0.290	0.271	0.139	0.289	0.291	-0.000		-0.206	0.025
Cover	-0.555	-0.321	-0.374	-0.504	0.755	-0.194	-0.278	-0.711	-0.849	0.024	-0.265		-0.049
Disp	0.124	0.058	0.085	0.124	-0.315	0.310	0.148	0.340	0.265	0.029	0.061	-0.187	

6.1. Firm size

Shynkevich (2012a) shows that trading rules work better for small-cap portfolios than technology industry portfolios, Shynkevich (2012b) shows that those rules may work for the small stocks but not for large stocks, and Han et al. (2013) show that the MA strategy is effective for both size and volatility decile portfolios. Since Table 8 reports that the Pearson correlation coefficient between PIN and firm size is -0.587, it is worth examining the profitability of MA strategies for information measure portfolios while controlling for firm size. To this end, we use a two-dimensional independent sorting approach to form 16 size-PIN portfolios using $n-1$ year-end data and apply MA strategies to the returns in Eq. (9) in year n. Table 9 reports the results.

Panel A shows the return difference, $R^d_{j,m,L}$, of the 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-sized portfolios generate higher MA returns, we will observe a decline in $R^d_{j,m,L}$ and α_j from the left to right with a rise in the market value of equity. This occurs in the last two row with the highest PIN, in which the small-sized portfolios have the highest $R^d_{j,m,L}$, and the declining pattern of α_j is also in the highest PIN groups. However, the relationship is reverse among the lowest PIN groups. This means that the evidence is mixed for the benefit from the MA strategy for small-sized portfolios once we control for the level of PIN. On the other hand, the return difference from the high-PIN rows is often higher than that from the low-PIN rows, with the high-minus-low return as high as 1.393% for the small-size groups, and the difference returns are also significant under the Stepwise SPA test in three out of four size categories.[14] In addition, the alphas for the highest-PIN portfolios are positively significant except for the third quartile size group. This indicates that after controlling for firm size, the MA strategy works for high-PIN portfolios.

Panel B presents the results from the MA (50) strategy. We find that the returns generally become small, which is consistent with the findings in Sections 4 and 5. high-minus-low-PIN return difference and alphas are positive in the smallest and largest groups, and small-minus-big-size returns and alpha are positive except for the lowest PIN groups. In sum, the evidence largely supports that high-PIN portfolios perform better than low-PIN portfolios using MA strategies, even after controlling for firm sizes.

6.2. Volatility measures

This section examines the effectiveness of the MA strategy in the case of portfolios sorted on the basis of PIN and volatility. We examine both returns and income volatilities. Return volatility (STD) is defined as the standard deviation of daily returns. We form 16 portfolios on the basis of STD and PIN in year $n-1$ and apply the MA strategy in year n. Panel A in Table 10 reports the difference returns and their alphas under the MA (10) strategy. The columns control for standard deviations. If the MA strategy performs better for high-volatility stocks, we expect the difference returns to increase from the left to the right columns. This property holds in all rows despite that the high-minus-low STD difference return in the first row is not significant. On the other hand, if the MA strategy performs better for high-PIN stocks, difference returns will be larger in the bottom rows than in the top rows, which is consistent with our findings. Alpha values are similar to those for high-volatility portfolios and larger than those for low-volatility portfolios. The alphas for high-PIN portfolios are greater than those for low-PIN portfolios.

Panel B presents the results for the MA (50) strategy, which are weaker than the MA (10) results in both difference returns and alphas. However, the difference returns and alphas of high-PIN portfolios remain larger than those of low-PIN's, and most of them pass the Stepwise SPA tests. The pattern is similar but weaker for the high-minus-low STD of difference returns and alphas.

As far as the income volatility (IVO) is concerned, we follow Han et al. (2013) to firstly compute the ratio of quarterly operating income to end-of-quarter total assets. We then subtract the ratio in the last quarter from that in the present quarter. IVO is accordingly defined as the standard deviation of the differences in the ratio

[14] The null hypothesis of the Stepwise SPA test is that the difference returns (alphas) of the four high-minus-low PIN and four small-minus-big size portfolios are all zero. The Stepwise SPA tests in the remaining of this section are implemented in a similar way.

Table 9
Two-Way Classification with Firm Size. This table reports the performance of 4 × 4 PIN-MV (firm size) portfolios under both the MA (10) and MA (50) strategies. For each strategy, it presents the difference returns $R^d_{j,m,L}$ and their alphas for the six-factor model. T-values (in parentheses) for $R^d_{j,m,L}$ are computed by bootstrapping and those for alphas are adjusted by Newey and West (1987) method. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$					α_j				
	MV	Small	2	3	Big	S-B	Small	1	3	Big	S-B
Panel A: Results for MA (10) Strategy											
PIN	Low	-0.808 **	-0.194	0.030	-0.360 ***	-0.448 *	-0.418 ***	0.377 **	0.518 ***	0.075	-0.503 *
		(-2.76)	(-0.97)	(0.16)	(-2.53)	(-1.62)	(-1.36)	(1.86)	(3.24)	(0.53)	(-1.79)
	2	-0.088	0.217	0.119	-0.153	0.066	0.368	0.736 ***	0.638 ***	0.315 ***	0.053
		(-0.29)	(0.92)	(0.54)	(-0.99)	(0.22)	(1.26)	(3.17)	(2.84)	(1.79)	(0.15)
	3	0.250 *	0.217	0.156	-0.009	0.259 *	0.734 ***	0.691 ***	0.643 ***	0.423 **	0.311
		(1.08)	(0.91)	(0.75)	(-0.04)	(1.34)	(3.69)	(2.74)	(3.15)	(2.47)	(1.45)
	High	0.585 ***	0.323	0.302	0.212 *	0.373 **	0.994 ***	0.852 ***	0.771 ***	0.550 ***	0.426 **
		(3.26)	(1.41)	(1.37)	(1.05)	(1.87)	(6.09)	(3.74)	(3.83)	(2.57)	(1.64)
	H-L	1.393 ***	0.517 ***	0.272	0.572 ***		1.423 ***	0.474 **	0.253	0.493 ***	
		(5.05) ###	(2.93) ##	(1.56)	(3.71) ###		(5.50)	(2.28)	(1.35)	(2.56)	
Panel B: Results for MA (50) Strategy											
PIN	Low	-0.178	-0.002	-0.068	-0.252 ***	0.073	0.148 ***	0.580 ***	0.406 ***	0.138 ***	-0.028
		(-0.69)	(-0.01)	(-0.44)	(-2.04)	(0.35)	(0.53)	(4.24)	(3.00)	(1.23)	(-0.11)
	2	0.128	0.047	-0.043	-0.227 **	0.355 **	0.612 ***	0.558 ***	0.492 ***	0.196	0.417 *
		(0.59)	(0.27)	(-0.27)	(-1.76)	(1.71)	(2.67)	(2.92)	(2.85)	(1.24)	(1.40)
	3	0.248 ***	0.074	-0.056	-0.216 *	0.464 ***	0.698 ***	0.602 ***	0.436 ***	0.121	0.577 ***
		(1.43)	(0.41)	(-0.36)	(-1.44)	(2.59) #	(4.51)	(2.87)	(2.43)	(0.63)	(2.65)
	High	0.283 ***	0.039	0.030	-0.064	0.347 **	0.680 ***	0.554 ***	0.519 ***	0.414	0.261 *
		(2.17)	(0.18)	(0.16)	(-0.32)	(2.03)	(4.65)	(2.22)	(3.52)	(1.94)	(1.11)
	H-L	0.461 **	0.041	0.098	0.188 ***		0.570 ***	-0.025	0.113	0.262 **	
		(2.45) #	(0.20)	(0.60)	(1.20)		(2.86) #	(-0.10)	(0.59)	(1.37)	

Table 10
Two-Way Classification with Return Volatility. This table reports the performance of 4 × 4 PIN-STD (return volatility) portfolios under both the MA (10) and MA (50) strategies. For each strategy, it presents the difference returns $R^d_{j,m,L}$ and their alphas for the six-factor model. T-values (in parentheses) for $R^d_{j,m,L}$ are computed by bootstrapping and those for alphas are adjusted by Newey and West (1987) method. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$					α_j				
	STD	Low	2	3	High	H-L	Low	2	3	High	H-L
Panel A: Results for MA (10) Strategy											
PIN	Low	-0.383 **	-0.127	0.104	-0.106	0.277	-0.063	0.425 ***	0.664 ***	0.429 *	0.492
		(-3.01)	(-0.72)	(0.50)	(-0.41)	(1.13)	(-0.45)	(2.49)	(3.55)	(1.79)	(1.84)
	2	-0.192	-0.020	0.166	0.451 **	0.643 **	0.173	0.485 **	0.738 **	1.085 ***	0.912 *
		(-1.20)	(-0.09)	(0.72)	(1.72)	(2.39) #	(0.80)	(2.34)	(3.35)	(3.90)	(2.77)
	3	-0.074	0.020	0.202	0.411 **	0.485 ***	0.298	0.477 *	0.674 **	0.965 ***	0.666 ***
		(-0.44)	(0.09)	(0.83)	(1.73)	(2.66) #	(1.54)	(2.16)	(2.78)	(4.71)	(3.23) #
	High	0.220	0.467 ***	0.615 ***	0.666 ***	0.445 *	0.554 **	0.894 ***	1.039 ***	1.095 ***	0.540 *
		(1.32)	(2.54)	(3.00)	(3.26)	(2.16)	(2.69)	(4.56)	(5.55)	(6.47)	(2.54)
	H-L	0.603 ***	0.594 ***	0.511 ***	0.772 ***		0.618 ***	0.469 ***	0.374 ***	0.666 ***	
		(6.35) ###	(4.99) ###	(4.57) ###	(4.21) ###		(5.10) ###	(3.36) #	(2.91)	(3.89) ##	
Panel B: Results for MA (50) Strategy											
PIN	Low	-0.165 **	-0.181 **	-0.177	0.017	0.182 **	0.152 **	0.346 ***	0.372 **	0.509 ***	0.357 **
		(-1.82)	(-1.34)	(-0.92)	(0.09)	(1.12)	(1.64)	(2.78)	(1.96)	(2.34)	(1.54)
	2	-0.087	-0.040	-0.016	0.098	0.185 *	0.266 *	0.455 ***	0.539 **	0.663 ***	0.397 **
		(-0.78)	(-0.27)	(-0.08)	(0.48)	(1.00)	(1.94)	(3.04)	(2.56)	(3.23)	(1.80)
	3	-0.042	-0.028	0.117	0.194 **	0.236 ***	0.309 **	0.456 ***	0.624 ***	0.713 ***	0.404 **
		(-0.35)	(-0.19)	(0.70)	(1.07)	(1.77) ##	(2.15)	(3.26)	(3.82)	(4.28)	(2.20) #
	High	0.152 **	0.291 ***	0.409 ***	0.277 ***	0.124	0.482 ***	0.708 ***	0.864 ***	0.650 ***	0.168
		(1.30)	(1.87)	(2.36)	(2.02)	(0.92)	(3.34)	(4.86)	(5.68)	(3.67)	(0.90)
	H-L	0.317 ***	0.472 ***	0.586 ***	0.260 **		0.330 ***	0.362 ***	0.492 ***	0.141	
		(4.44) ###	(4.56) ###	(4.67) ###	(2.03) ##		(3.37) ###	(2.97) ##	(3.30) ###	(0.97)	

over a five-year period. We use portfolios sorted on the basis of IVO between year $n-1$ and $n-5$ and PIN estimated in $n-1$ to implement the MA strategies in n.

Table 11 reports the result for the 16 portfolios sorted as per the information measures and IVO. Panel A reports the difference returns and alphas for the PIN-IVO portfolios under the MA (10) strategy. While the high-PIN portfolios perform better than the low-PIN ones in both return difference and alpha, the evidence for high-IVO portfolios is weak, especially in the low-PIN groups. Panel B reports the results for the MA (50) strategy. Here as well, high-PIN portfolios perform well and high-IVO portfolios do not. Tables 10 and 11 suggest that high-PIN portfolios perform well under the MA strategy even after controlling for returns or income volatilities.

6.3. Liquidity measures

Table 8 shows a positive correlation between information measures and liquidity proxies, and scholars have long indicated that liquidity provisions can be partially explained by the profitability

Table 11
Two-Way Classification with Income Volatility. This table reports the performance of 4 × 4 PIN-IVOL (operating income volatility) portfolios under both the MA (10) and MA (50) strategies. For each strategy, it presents the difference returns $R^d_{j,m,L}$ and their alphas for the six-factor model. T-values (in parentheses) for $R^d_{j,m,L}$ are computed by bootstrapping and those for alphas are adjusted by Newey and West (1987) method. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$										α_j								
	IVOL	Low		2		3		High		H-L		Low		2		3		High		H-L
Panel A: Results for MA (10) Strategy																				
PIN	Low	-0.385	***	-0.277	**	-0.310	***	-0.321	***	0.063		0.075		0.138		0.132		0.135		0.060
		(-2.49)		(-1.91)		(-1.85)		(-1.96)		(0.41)		(0.48)		(0.91)		(0.85)		(0.81)		(0.31)
	2	-0.061		-0.018		-0.014		0.055		0.115		0.404		0.508	**	0.512	***	0.596	***	0.192
		(-0.29)		(-0.09)		(-0.07)		(0.29)		(0.68)		(1.85)		(2.72)		(2.83)		(3.28)		(0.93)
	3	-0.132		0.002		0.200		0.226	**	0.358	*	0.328		0.526	**	0.702	**	0.751	***	0.423
		(-0.62)		(0.01)		(0.85)		(1.20)		(2.29)		(1.50)		(2.46)		(3.13)		(4.78)		(2.21)
	High	0.242	**	0.267	**	0.475	***	0.438	***	0.197		0.687	***	0.716	***	0.914	***	0.839	***	0.152
		(1.54)		(1.37)		(2.97)		(2.35)		(0.98)		(3.98)		(3.88)		(5.63)		(5.48)		(0.67)
	H-L	0.627	***	0.545	***	0.785	***	0.760	***			0.612	***	0.578	***	0.782	***	0.704	***	
		(5.11)	###	(4.34)	##	(6.83)	###	(4.45)	##			(3.83)	##	(4.43)	##	(6.11)	###	(4.36)	##	
Panel B: Results for MA (50) Strategy																				
PIN	Low	-0.270	***	-0.187	**	-0.239	***	-0.209	***	0.061	*	0.150	*	0.198	***	0.182	**	0.224	**	0.075
		(-2.37)		(-1.63)		(-1.93)		(-1.53)		(0.70)		(1.31)		(1.87)		(1.50)		(1.36)		(0.60)
	2	-0.207	*	-0.120		-0.068		-0.117		0.090	**	0.276	*	0.411	***	0.435	***	0.357	***	0.081
		(-1.45)		(-0.81)		(-0.48)		(-0.78)		(1.01)		(1.84)		(2.61)		(2.73)		(2.18)		(0.77)
	3	-0.217	*	0.021		-0.018		0.013		0.230	**	0.268		0.522	***	0.434	***	0.500	***	0.232
		(-1.39)		(0.13)		(-0.11)		(0.08)		(1.69)	#	(1.31)		(2.90)		(2.85)		(3.82)		(1.26)
	High	0.121	*	0.101		0.232	***	0.225	***	0.104		0.581	***	0.573	***	0.646	***	0.570	***	-0.011
		(0.92)		(0.64)		(1.79)		(1.56)		(1.06)		(4.55)		(4.06)		(4.39)		(3.77)		(-0.07)
	H-L	0.392	***	0.288	***	0.471	***	0.434	***			0.432	***	0.375	***	0.464	***	0.346	**	
		(4.35)	###	(2.86)	###	(4.66)	###	(3.19)	###			(4.59)	###	(3.67)	###	(3.62)	###	(1.93)	#	

of technical analysis. Kavajecz and Odders-White (2004), for example, state that MA signals correspond to shifts in the depth of the limit order book. Osler (2003) uses order flows to explain technical trading in currency markets. From a theoretical perspective, Garleanu and Pedersen (2003) and Vayanos and Wang (2011) highlight that asymmetric information can result in illiquidity. It is, therefore, worth exploring the performance of portfolios formed by liquidity proxies and subject to MA strategies.

We examine four liquidity proxies. First is quoted spread (QSP), defined as the difference between the national best ask and bid quotes divided by their midpoint. We calculate the time-weighted average QSP for each day and then the annual spread by averaging the daily spreads. Second is Amihud (2002) illiquidity measure (Illiq), defined as the annual average of the daily absolute rate of return divided by the dollar volume. Third, following Pastor and Stambaugh (2003), we run a regression of current excess returns on past returns and past signed volumes:

$$R^e_{i,t} = \beta_{i,0} + \beta_{i,1} R_{i,t-1} + \gamma_i \mathrm{sign}(R^e_{i,t-1}) v_{i,t-1} + \varepsilon_{i,t}, \tag{16}$$

where $R^e_{i,t} = R_{i,t} - R_{M,t}$ is the return on stock i in excess of market return on date t and $v_{i,t-1}$ is the dollar trading volume on $t-1$. The illiquidity measure, Gamma or $\hat{\gamma}_i$, is the estimated coefficient of the signed volumes.

Finally, we use PSOS derived from model (5) to measure the fraction of trades originating from order-flow shocks:

$$PSOS = \frac{l(\Delta_b + \Delta_s)}{a((1-d)u_b + du_s) + l(\Delta_b + \Delta_s) + \epsilon_b + \epsilon_s}. \tag{17}$$

We sort portfolios by liquidity proxies and PIN for $n-1$ into 16 portfolios and examine the performance of the MA strategies. Panel A in Table 12 reports $R^d_{j,m,L}$ and α_j for the MA (10) strategy. High-minus-low PIN difference returns and alpha are positively significant in most of the categories, and half of them pass the Stepwise SPA tests. By contrast, large QSP portfolios report negative difference returns when PIN is low and positive differences when PIN is high. We observe similar patterns for the alphas. The results for the MA (50) strategy are weaker, although the difference returns and alphas generally remain higher in high-PIN groups than in low-PIN groups. This indicates that PIN is a better variable than QSP when forming separate portfolios for high and low MA returns.

Table 13 reports the results for the 16 portfolios sorted on the basis of Illiq and PIN. The findings are similar to those in Table 12. High-PIN portfolios perform better than low-PIN ones and there is no discernible pattern for the Illiq portfolios. Table 14 presents the results for the 16 portfolios sorted as per Gamma and PIN. Most of the high-minus-low PIN difference returns and alpha are positively significant and pass the Stepwise SPA test. On the other hand, the significant difference returns or alphas for illiquid-minus-liquid portfolios are rare.

Table 15 lists the results for PSOS, which is arguably the most successful liquidity variable examined in this section. Panel A presents the results for the MA (10) strategy in the case of PIN-PSOS portfolios. All high-minus-low-PSOS difference returns and alphas are positive and statistically significant, and they all pass the Stepwise SPA tests. PIN also performs well; that is, all high-minus-low difference returns and alphas are significantly positive. Panel B shows the results for PIN-PSOS portfolios under the MA (50) strategy. The results for the high-minus-low PIN portfolios remain strong; the performance of the high-minus-low PSOS portfolios is less impressive. Nevertheless, three out of four high-minus-low-PIN difference returns and alphas remain significant.

Since PSOS is derived from the Adjusted PIN model, it is interesting to compare its performance with alternative information measures. Panels C, D, and E present the results of applying the MA (10) strategy to the PIN_B, PIN_G, and Adjusted PIN portfolios with PSOS. PSOS reports consistently good performance. After controlling for the effects of the three information measures, high PSOS portfolios show larger difference returns and alphas than those of low PSOS portfolios. The information measures, however, reports mixed performance: PIN_G performs as well as PIN in Panel A; Adjusted PIN shows some significance in high-minus-low differences; and PIN_B performs the poorest among the three, of which high-

Table 12
Two-Way Classification with Quoted Spread. This table reports the performance of 4 × 4 PIN-QSP (quoted spread) portfolios under both the MA (10) and MA (50) strategies. For each strategy, it presents the difference returns $R^d_{j,m,L}$ and their alphas for the six-factor model. T-values (in parentheses) for $R^d_{j,m,L}$ are computed by bootstrapping and those for alphas are adjusted by Newey and West (1987) method. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$					α_j				
	QSP	Small	2	3	Big	B-S	Small	2	3	Big	B-S
Panel A: Results for MA (10) Strategy											
PIN	Low	-0.368***	-0.042	-0.077	-1.080***	-0.712***	0.050***	0.482***	0.403***	-0.722	-0.772***
		(-2.71)	(-0.23)	(-0.36)	(-4.88)	(-3.02)	(0.40)	(3.05)	(2.20)	(-3.06)	(-3.05)
	2	-0.212	0.103	0.001	-0.222	-0.010	0.241***	0.646***	0.522***	0.194**	-0.047
		(-1.33)	(0.48)	(0.00)	(-0.82)	(-0.03)	(1.31)	(3.05)	(2.35)	(0.68)	(-0.14)
	3	-0.179	0.050	0.196	0.182	0.361	0.183**	0.550***	0.741***	0.606***	0.422
		(-1.01)	(0.23)	(0.86)	(0.81)	(1.61)	(0.81)	(2.48)	(3.39)	(2.96)	(1.46)
	High	0.209	0.328*	0.215	0.484***	0.275	0.590***	0.877***	0.699***	0.892***	0.290
		(0.96)	(1.42)	(0.84)	(2.55)	(1.08)	(2.25)	(3.92)	(2.85)	(5.37)	(0.88)
	H-L	0.577***	0.379***	0.283	1.564***		0.553***	0.411***	0.295	1.614***	
		(3.19)##	(2.47)	(1.63)	(5.67)###		(2.31)	(2.49)#	(1.46)	(6.04)###	
Panel B: Results for MA (50) Strategy											
PIN	Low	-0.241***	-0.107	-0.063	-0.336**	-0.095	0.164***	0.361***	0.440***	0.056***	-0.108
		(-1.98)	(-0.73)	(-0.43)	(-1.69)	(-0.54)	(1.41)	(2.54)	(3.98)	(0.28)	(-0.62)
	2	-0.180*	-0.119	0.080	-0.057	0.123	0.285***	0.429***	0.617***	0.354***	0.069
		(-1.44)	(-0.69)	(0.48)	(-0.28)	(0.66)	(2.00)	(2.31)	(3.90)	(1.61)	(0.32)
	3	-0.266**	0.054	0.044	0.084	0.350***	0.058***	0.553***	0.590***	0.495***	0.437***
		(-1.83)	(0.34)	(0.25)	(0.48)	(2.42)#	(0.31)	(3.27)	(3.20)	(2.92)	(2.48)#
	High	0.039	-0.146	0.136	0.232***	0.193	0.634***	0.418***	0.714***	0.620***	-0.007
		(0.18)	(-0.67)	(0.70)	(1.70)	(0.96)	(3.02)	(2.14)	(4.16)	(4.20)	(-0.02)
	H-L	0.280***	-0.047	0.186*	0.568***		0.452***	0.054	0.274***	0.564***	
		(1.66)	(-0.33)	(1.58)	(3.80)###		(2.32)#	(0.34)	(1.94)	(4.23)###	

Table 13
Two-Way Classification with Amihud's Illiquidity. This table reports the performance of 4 × 4 PIN-Illiq (Amihud measure) portfolios under both the MA (10) and MA (50) strategies. For each strategy, it presents the difference returns $R^d_{j,m,L}$ and their alphas for the six-factor model. T-values (in parentheses) for $R^d_{j,m,L}$ are computed by bootstrapping and those for alphas are adjusted by Newey and West (1987) method. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$					α_j				
	Illiq	Liquid	2	3	Illiquid	I-L	Liquid	2	3	Illiquid	I-L
Panel A: Results for MA (10) Strategy											
PIN	Low	-0.349***	-0.028	-0.074	-0.911***	-0.562**	0.105	0.512***	0.263	-0.536**	-0.641**
		(-2.38)	(-0.15)	(-0.33)	(-3.57)	(-2.07)	(0.72)	(3.22)	(1.08)	(-2.00)	(-2.22)
	2	-0.029	0.189	-0.004	-0.348*	-0.319	0.439*	0.744**	0.478*	0.004	-0.434
		(-0.17)	(0.88)	(-0.01)	(-1.26)	(-1.19)	(2.41)	(3.28)	(2.18)	(0.01)	(-1.48)
	3	-0.040	0.246	0.202	0.046	0.086	0.322	0.763**	0.708**	0.446***	0.124
		(-0.19)	(1.19)	(0.92)	(0.24)	(0.43)	(1.39)	(3.60)	(3.26)	(2.41)	(0.51)
	High	0.324***	0.178	0.296	0.516***	0.192	0.727***	0.644**	0.789**	0.913***	0.165
		(1.42)	(0.70)	(1.33)	(2.91)	(0.83)	(2.90)	(2.65)	(3.61)	(5.77)	(0.57)
	H-L	0.673***	0.206	0.381***	1.427***		0.645***	0.131	0.534**	1.449***	
		(3.41)##	(1.08)	(1.91)	(4.84)###		(2.59)##	(0.63)	(2.08)	(4.74)###	
Panel B: Results for MA (50) Strategy											
PIN	Low	-0.254***	-0.058	-0.022	-0.382**	-0.129	0.140**	0.408***	0.336*	0.021	-0.119
		(-2.09)	(-0.44)	(-0.09)	(-1.77)	(-0.67)	(1.17)	(3.14)	(1.55)	(0.10)	(-0.65)
	2	-0.199**	-0.049	0.008	-0.138	0.061	0.268**	0.483***	0.543***	0.188*	-0.080
		(-1.50)	(-0.30)	(0.04)	(-0.70)	(0.31)	(1.69)	(2.88)	(3.14)	(0.88)	(-0.35)
	3	-0.283**	0.113	0.047	0.062	0.345***	0.080	0.602***	0.566***	0.422***	0.342*
		(-1.78)	(0.73)	(0.26)	(0.39)	(2.13)#	(0.34)	(3.81)	(3.20)	(2.64)	(1.47)
	High	0.027	-0.107	0.200	0.300***	0.272**	0.609***	0.443**	0.712***	0.657***	0.050
		(0.13)	(-0.52)	(1.19)	(2.37)	(1.49)	(2.71)	(2.44)	(4.73)	(4.88)	(0.21)
	H-L	0.281***	-0.049	0.233**	0.682***		0.454***	0.036	0.384**	0.636***	
		(1.71)	(-0.30)	(1.10)	(3.92)##		(2.17)	(0.19)	(1.55)	(3.94)##	

minus-low differences report varying signs and they are often not significant.

6.4. Analyst following

Here, we examine portfolios sorted by PIN and analysts-related variables. Table 16 presents the results for analyst coverage (Cover), defined as the number of analysts that follow a security in $n-1$. We also use the information measures to sort the 16 portfolios. Panel A reports the difference returns and their alphas for the MA (10) strategy. Analyst coverage helps investors understand securities, and thus, lower analyst following indicates greater information uncertainty. If higher uncertainty improves the performance of the technical analysis, as Han et al. (2013) predict, then the difference returns and alphas decrease from the left to the right columns. However, this is not always the case in Panel A, where the returns and alphas of the least covered portfolios are signifi-

Table 14
Two-Way Classification with Pastor and Stambaugh (2003) Measure. This table reports the performance of 4 × 4 PIN-Gamma (Pástor-Stambaugh measure) portfolios under both the MA (10) and MA (50) strategies. For each strategy, it presents the difference returns $R^d_{j,m,L}$ and their alphas for the six-factor model. T-values (in parentheses) for $R^d_{j,m,L}$ are computed by bootstrapping and those for alphas are adjusted by Newey and West (1987) method. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$										α_j									
	Gamma	Liquid		2		3		Illiquid		I-L		Liquid		2		3		Illiquid		I-L	
Panel A: Results for MA (10) Strategy																					
PIN	Low	-0.626	***	-0.243	**	-0.337	***	-0.451	***	0.174	*	-0.123		0.219	*	0.122		-0.018		0.105	
		(-2.95)		(-1.67)		(-2.33)		(-2.09)		(0.97)		(-0.54)		(1.59)		(0.90)		(-0.07)		(0.55)	
	2	-0.165		-0.006		0.050		0.037		0.203	*	0.256	*	0.517	*	0.608	**	0.555	***	0.299	***
		(-0.84)		(-0.03)		(0.27)		(0.18)		(1.51)	#	(1.27)		(2.54)		(3.24)		(2.76)		(2.12)	##
	3	0.146		0.142		0.118		0.109		-0.037		0.620	***	0.656	**	0.604	*	0.602	***	-0.017	
		(0.75)		(0.66)		(0.62)		(0.53)		(-0.43)		(3.39)		(2.95)		(2.85)		(2.99)		(-0.15)	
	High	0.487	***	0.151		0.074		0.506	***	0.018		0.926	***	0.638	***	0.475	***	0.958	***	0.032	
		(2.76)		(0.68)		(0.36)		(2.96)		(0.25)		(5.45)		(2.90)		(2.56)		(6.48)		(0.42)	
	H-L	1.113	***	0.394	***	0.411	***	0.957	***			1.049	***	0.420	***	0.354	**	0.976	***		
		(6.29)	###	(2.50)	###	(2.69)	###	(6.22)	###			(5.43)	###	(2.39)	##	(2.18)	##	(5.76)	###		
Panel B: Results for MA (50) Strategy																					
PIN	Low	-0.192	*	-0.203	**	-0.289	***	-0.225	**	-0.033		0.265	***	0.266	***	0.132	*	0.156	*	-0.109	
		(-1.17)		(-1.63)		(-2.36)		(-1.50)		(-0.24)		(1.81)		(2.66)		(0.97)		(1.02)		(-0.72)	
	2	-0.060		-0.109		-0.145		-0.057		0.003		0.363	***	0.406	***	0.372	**	0.453	***	0.090	
		(-0.43)		(-0.76)		(-0.94)		(-0.40)		(0.03)		(2.38)		(2.41)		(2.16)		(2.92)		(0.80)	
	3	0.025		-0.084		-0.121		0.071		0.046		0.477	***	0.388		0.334	**	0.557	***	0.080	
		(0.17)		(-0.47)		(-0.77)		(0.44)		(0.65)		(2.91)		(1.69)		(1.87)		(3.66)		(0.98)	
	High	0.286	***	0.130	*	-0.096		0.265	***	-0.021		0.675	***	0.670	***	0.326	*	0.663	***	-0.013	
		(2.26)		(0.73)		(-0.59)		(2.04)		(-0.31)		(4.92)		(5.11)		(1.82)		(5.23)		(-0.15)	
	H-L	0.479	***	0.334	***	0.193	**	0.491	***			0.410	***	0.404	***	0.194		0.507	***		
		(4.42)	###	(2.89)	###	(1.51)		(4.40)	###			(3.25)	###	(3.67)	###	(1.20)		(4.41)	###		

cantly larger than those of the most covered portfolio only when PIN is high. On the other hand, high-PIN portfolios consistently report higher returns and alphas than those of low-PIN portfolios. We also observe this pattern for the MA (50) strategy in Panel B.

The final exercise examines the performance of the portfolios sorted on the basis of PIN and analysts forecasts dispersion. Dispersion (Disp) is the standard deviation of analysts' $n-1$ forecasts of earnings per share for year n divided by the $n-1$ closing price. Table 17 presents the results for the case of PIN-Disp portfolios.

Panels A and B report the difference returns and their alphas for the MA (10) and MA (50) trading strategies. If dispersion is an indicator of information uncertainty, then high-dispersion portfolios are expected to exhibit larger difference returns and alphas. The wide-minus-narrow dispersion results are significant for the difference returns and alphas dispersion portfolios in all categories and pass the Stepwise SPA tests except for the high-PIN portfolios. The PIN results, however, are not impressive. Although the returns While the high-minus-low difference returns and alphas are all positive, they are significant only in the widest and narrowest Disp categories. While the results appear to be favorable for Disp, the use of analyst data shrinks the sample size by half in the early period and by one-third in the later period, implying that the application of Disp is somewhat limiting.

7. How about other technical signals?

The analysis so far has revealed that the success of technical analysis is by no means universal; it works in the portfolios with high level of information asymmetry. The investigations above, however, focus on the moving average strategy, and readers may wonder if similar results can be found in other technical rules. As dozens if not hundreds of technical signals have been developed, a comprehensive survey of all of them is certainly beyond the scope of this paper. Therefore, we focus on the three technical rules that have been often examined in the academic literature (See Sullivan et al. (1999)), namely, the filter rule, the support and resistance rule, and the channel breakout rule.

7.1. Filter

We follow Sullivan et al. (1999) to define the three technical rules. The filter rule involves buying when the price goes up by x percent from the recent n-day minimum and selling when the price does down by x percent from the recent n-day maximum. Although there are a few variants with the filter rule, for example, we focus on a few trading strategies of which the range of the number of signals is comparable to the MA strategies.[15] Specifically, we choose $x = 1, 2, 5$ and $n = 10, 20, 50$ and the results are reported in Table 18.

To save the space, the table only presents the results from the highest and lowest PIN decile portfolios and their differences, constructed by value- and equally-weighted methods. Most of the high-minus-low difference returns are significantly positive, and more than half of them pass the Stepwise SPA test.[16] However, it appears that the positive high-minus-low returns are mainly due to the negative returns from the low-PIN portfolios. Although six out of nine equally-weighted high-PIN portfolios exhibit significantly positive returns, only two of their value-weighted counterparts do. The picture of the six-factor alphas is similar to the difference return in that the majority of high-minus-low alphas are significantly positive and pass the Stepwise SPA test. The difference is that there are many positive alphas for both the equally- and value-weighted high-PIN portfolios, and none of the low-PIN portfolio alphas are significant. To sum up, high-PIN portfolios perform better than low-PIN portfolios when the filter rule is implemented.

[15] The average number of trades for the MA strategies is between 9 and 41 per year (see Table 6), and it is between 2.9 and 149 for the filter strategies presented below.

[16] The null hypothesis is that none of the high-minus-low returns reported in this table are significantly positive.

Table 15

Two-Way Classification with PSOS. This table reports the performance of PIN-PSOS portfolios with both MA (10) and MA (50) strategies, as well as that for PIN_B-PSOS, PIN_G-PSOS, and Adjusted-PIN-PSOS portfolios under the MA (10) strategies. For each strategy, it presents the difference returns $R^d_{j,m,L}$ and their alphas for the six-factor model. T-values (in parentheses) for $R^d_{j,m,L}$ are computed by bootstrapping and those for alphas are adjusted by Newey and West (1987) method. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$					α_j				
	PSOS	Low	2	3	High	H-L	Low	2	3	High	H-L
Panel A: MA (10) Strategy for PIN											
PIN	Low	-0.385 ***	-0.363 **	-0.165	-0.205	0.180 *	0.006 ***	0.103 ***	0.348 ***	0.297 ***	0.290 ***
		(-3.18)	(-2.14)	(-0.96)	(-0.95)	(1.26) #	(0.04)	(0.63)	(2.24)	(1.51)	(2.05) ##
	2	-0.246 *	-0.076	-0.016	0.250	0.496 ***	0.234 ***	0.410 ***	0.551 ***	0.810 ***	0.576 ***
		(-1.46)	(-0.41)	(-0.08)	(1.14)	(3.36) ###	(1.17)	(2.15)	(2.85)	(4.29)	(3.58) ###
	3	-0.082	0.016	0.188	0.295	0.377 ***	0.366 ***	0.499 ***	0.698 ***	0.802 ***	0.436 ***
		(-0.44)	(0.08)	(0.81)	(1.40)	(4.11) ###	(2.12)	(2.54)	(3.28)	(4.19)	(4.37) ###
	High	0.194 **	0.098	0.393 ***	0.609 ***	0.414 ***	0.583 ***	0.525 ***	0.836 ***	1.056 ***	0.472 ***
		(1.13)	(0.49)	(2.07)	(3.20)	(3.91) ###	(3.59)	(2.60)	(5.10)	(5.86)	(3.68) ###
	H-L	0.579 ***	0.461 **	0.558 ***	0.814 ***		0.577 ***	0.423 **	0.488 ***	0.759 ***	
		(4.04) ###	(2.83) ##	(4.27) ###	(5.12) ###		(3.80) ###	(2.53) ##	(3.59) ###	(4.37) ###	
		$R^d_{j,m,L}$					α_j				
	PSOS	Low	2	3	High	H-L	Low	2	3	High	H-L
Panel B: MA (50) Strategy for PIN											
PIN	Low	-0.235 ***	-0.259 **	-0.238 ***	-0.085	0.150 **	0.151 ***	0.164 ***	0.202 ***	0.374 ***	0.223 ***
		(-2.20)	(-2.03)	(-1.85)	(-0.53)	(1.49) ##	(1.38)	(1.14)	(1.73)	(2.46)	(2.09) ##
	2	-0.117	-0.207 *	0.007	-0.101	0.016	0.327 ***	0.292 ***	0.564 ***	0.289 ***	-0.039
		(-0.89)	(-1.45)	(0.04)	(-0.55)	(0.14)	(2.03)	(1.68)	(3.44)	(1.42)	(-0.28)
	3	-0.014	0.007	0.042	0.057	0.071 **	0.425 ***	0.467 ***	0.536 ***	0.523 ***	0.098 **
		(-0.08)	(0.05)	(0.24)	(0.34)	(0.92)	(2.75)	(2.95)	(3.45)	(3.10)	(1.17)
	High	0.114	0.001	0.303 ***	0.337 ***	0.224 ***	0.527 ***	0.441 ***	0.766 ***	0.753 ***	0.227 ***
		(0.73)	(0.00)	(1.98)	(2.51)	(2.30) ##	(3.35)	(2.85)	(6.05)	(5.41)	(1.84) #
	H-L	0.348 ***	0.260 **	0.541 ***	0.422 ***		0.376 ***	0.277 **	0.563 ***	0.380 ***	
		(2.50) ###	(1.85) ##	(5.24) ###	(4.12) ###		(2.37) ##	(1.76) #	(5.13) ###	(3.28) ###	
Panel C: MA (10) Strategy for PIN_B											
PIN_B	Low	-0.257 *	-0.074	0.069	0.095	0.352 ***	0.130 ***	0.391 ***	0.584 ***	0.594 ***	0.463 ***
		(-1.63)	(-0.45)	(0.33)	(0.49)	(2.56)	(0.65)	(2.46)	(3.03)	(3.17)	(2.93)
	2	-0.195 *	-0.096	0.109	0.428 *	0.624 ***	0.288 ***	0.376 ***	0.646 ***	0.901 ***	0.612 ***
		(-1.34)	(-0.49)	(0.54)	(1.85)	(4.40) ###	(2.09)	(1.88)	(3.34)	(4.31)	(4.39) ##
	3	-0.148	-0.022	0.171	0.479 ***	0.627 ***	0.275 ***	0.480 ***	0.689 ***	0.973 ***	0.698 ***
		(-0.82)	(-0.11)	(0.86)	(2.53)	(4.96) ###	(1.43)	(2.91)	(3.93)	(5.91)	(4.82) ###
	High	-0.125	-0.136	0.039	0.315 ***	0.440 ***	0.274 ***	0.244 ***	0.462 ***	0.744 ***	0.470 ***
		(-0.85)	(-0.79)	(0.23)	(1.77)	(4.40) ###	(1.80)	(1.31)	(2.81)	(4.49)	(4.21) ##
	H-L	0.132	-0.062	-0.031	0.220 **		0.144	-0.148	-0.122 *	0.150	
		(0.92)	(-0.44)	(-0.24)	(2.02)		(0.81)	(-0.91)	(-0.90)	(1.28)	
		$R^d_{j,m,L}$					α_j				
	PSOS	Low	2	3	High	H-L	Low	2	3	High	H-L
Panel D: MA (10) Strategy for PIN_G											
PIN_G	Low	-0.362 ***	-0.372 ***	-0.153	-0.208 *	0.153 ***	0.061 ***	0.070 ***	0.335 ***	0.313 ***	0.252 ***
		(-2.79)	(-2.59)	(-0.86)	(-1.14)	(1.42) ###	(0.46)	(0.49)	(2.01)	(1.84)	(2.04) ###
	2	-0.146	-0.154	-0.068	0.130	0.276 ***	0.325 ***	0.293 ***	0.439 ***	0.615 ***	0.290 ***
		(-0.98)	(-0.84)	(-0.36)	(0.62)	(2.28) ###	(2.19)	(1.54)	(2.42)	(3.19)	(2.30) ###
	3	-0.122	0.007	0.124	0.382 **	0.504 ***	0.380 ***	0.531 ***	0.629 ***	0.872 ***	0.492 ***
		(-0.68)	(0.03)	(0.57)	(2.05)	(4.30) ###	(1.89)	(2.99)	(3.08)	(5.22)	(3.59) ###
	High	0.082	0.175	0.495 ***	0.539 ***	0.458 ***	0.431 ***	0.599 ***	0.943 ***	1.003 ***	0.572 ***
		(0.46)	(0.94)	(2.52)	(2.71)	(4.07) ###	(2.48)	(3.28)	(5.23)	(5.27)	(4.40) ###
	H-L	0.443 ***	0.547 ***	0.649 ***	0.748 ***		0.370 ***	0.529 ***	0.608 ***	0.690 ***	
		(3.69) ###	(4.56) ###	(4.66) ###	(6.12) ###		(2.79) ###	(4.01) ###	(3.76) ###	(5.51) ###	
Panel E: MA (10) Strategy for AdjPIN											
AdjPIN	Low	-0.365 ***	-0.291 ***	-0.114	0.161	0.525 ***	0.050 ***	0.133 ***	0.387 ***	0.649 ***	0.599 ***
		(-2.84)	(-1.88)	(-0.56)	(0.70)	(3.48) ###	(0.38)	(0.86)	(2.12)	(3.30)	(3.76) ###
	2	-0.219	-0.091	0.102	0.171	0.390 ***	0.245 ***	0.375 ***	0.616 ***	0.689 ***	0.444 ***
		(-1.24)	(-0.51)	(0.51)	(0.80)	(2.90) ##	(1.20)	(1.99)	(3.08)	(3.59)	(2.80) ##
	3	-0.250 *	0.008	0.165	0.208	0.458 ***	0.212 ***	0.467 ***	0.677 ***	0.722 ***	0.510 ***
		(-1.45)	(0.04)	(0.81)	(0.96)	(4.13) ###	(1.24)	(2.81)	(3.57)	(3.69)	(4.26) ###
	High	0.098	0.038	0.325 **	0.430 ***	0.332 ***	0.469 ***	0.489 ***	0.764 ***	0.860 ***	0.391 ***
		(0.56)	(0.20)	(1.76)	(2.28)	(3.35) ###	(2.67)	(2.82)	(4.69)	(4.84)	(3.37) ##
	H-L	0.463 ***	0.329 **	0.438 **	0.270 ***		0.419 ***	0.356 **	0.377 *	0.211 *	
		(3.43) ###	(2.22) ##	(2.73) ##	(2.00) ##		(2.66) #	(2.05)	(2.22)	(1.57)	

Table 16
Two-Way Classification with Analyst Coverage. This table reports the performance of 4 × 4 PIN-Cover (number of analysts) portfolios under both the MA (10) and MA (50) strategies. For each strategy, it presents the difference returns $R^d_{j,m,L}$ and their alphas for the six-factor model. T-values (in parentheses) for $R^d_{j,m,L}$ are computed by bootstrapping and those for alphas are adjusted by Newey and West (1987) method. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$					α_j				
	Cover	Least	2	3	Most	L-M	Least	2	3	Most	L-M
Panel A: Results for MA (10) Strategy											
PIN	Low	-0.439**	-0.054	-0.007	-0.342***	-0.098	-0.034	0.406**	0.527***	0.121	-0.155
		(-2.37)	(-0.26)	(-0.03)	(-2.42)	(-0.50)	(-0.17)	(2.07)	(2.78)	(0.91)	(-0.67)
	2	-0.030	-0.049	0.040	0.049	-0.079	0.440**	0.470*	0.572*	0.556***	-0.116
		(-0.13)	(-0.22)	(0.18)	(0.29)	(-0.39)	(1.82)	(2.08)	(2.34)	(3.32)	(-0.52)
	3	0.236*	0.203	0.299	0.048	0.188	0.653***	0.719**	0.794**	0.469*	0.184
		(1.19)	(0.92)	(1.35)	(0.23)	(1.08)	(3.44)	(3.30)	(3.67)	(2.25)	(0.86)
	High	0.612***	0.385**	0.207	-0.037	0.649***	0.967***	0.887***	0.675*	0.337*	0.609***
		(3.53)	(1.86)	(0.75)	(-0.17)	(3.60)##	(5.79)	(4.73)	(2.41)	(1.57)	(2.71)
	H-L	1.052***	0.439***	0.214	0.305***		1.001***	0.481***	0.148	0.240**	
		(5.65)###	(3.14)#	(1.00)	(1.99)		(4.89)###	(3.24)#	(0.69)	(1.40)	
Panel B: Results for MA (50) Strategy											
PIN	Low	-0.189*	-0.044	-0.089	-0.275***	0.086	0.227***	0.390***	0.394**	0.132**	0.095
		(-1.25)	(-0.30)	(-0.60)	(-2.45)	(0.80)	(1.56)	(2.74)	(2.51)	(1.17)	(0.75)
	2	0.028	-0.061	-0.033	-0.162*	0.190*	0.421***	0.421**	0.507**	0.326***	0.095
		(0.21)	(-0.36)	(-0.20)	(-1.19)	(1.56)	(2.39)	(2.36)	(2.50)	(2.79)	(0.60)
	3	0.092	0.115	0.097	-0.098	0.190**	0.523***	0.635***	0.614***	0.315***	0.207*
		(0.57)	(0.67)	(0.58)	(-0.65)	(1.49)	(3.24)	(3.98)	(3.70)	(2.02)	(1.28)
	High	0.274***	0.347***	0.107	-0.043	0.317***	0.616***	0.901***	0.661***	0.468***	0.142*
		(2.37)	(1.75)	(0.56)	(-0.23)	(2.17)##	(4.18)	(5.43)	(3.86)	(2.47)	(0.78)
	H-L	0.464***	0.392***	0.195***	0.233**		0.389***	0.511***	0.267***	0.325*	
		(4.54)###	(3.15)###	(1.47)	(1.61)		(3.89)###	(3.62)###	(2.07)	(1.91)	

Table 17
Two-Way Classification with Forecast Dispersion. This table reports the performance of 4 × 4 PIN-Disp (EPS forecast dispersion) portfolios under both the MA (10) and MA (50) strategies. For each strategy, it presents the difference returns $R^d_{j,m,L}$ and their alphas for the six-factor model. T-values (in parentheses) for $R^d_{j,m,L}$ are computed by bootstrapping and those for alphas are adjusted by Newey and West (1987) method. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$					α_j				
	Disp	Narrow	2	3	Wide	W-N	Narrow	2	3	Wide	W-N
Panel A: Results for MA (10) Strategy											
PIN	Low	-0.469***	-0.250**	-0.148	-0.070	0.399***	-0.108	0.179*	0.310**	0.506***	0.614***
		(-3.31)	(-1.50)	(-0.93)	(-0.36)	(2.99)#	(-0.64)	(1.14)	(2.08)	(3.15)	(4.38)##
	2	-0.268*	-0.142	-0.065	0.206	0.473***	0.137	0.358*	0.448**	0.820***	0.684***
		(-1.66)	(-0.78)	(-0.33)	(0.97)	(3.48)#	(0.73)	(1.83)	(2.39)	(4.23)	(4.49)##
	3	-0.214	-0.042	-0.119	0.202	0.416***	0.226	0.433	0.391	0.799***	0.573***
		(-1.08)	(-0.20)	(-0.57)	(0.90)	(3.00)#	(1.03)	(1.76)	(1.66)	(4.33)	(3.83)##
	High	-0.112	-0.070	0.035	0.205	0.317**	0.315	0.362	0.493**	0.731***	0.416**
		(-0.48)	(-0.28)	(0.16)	(1.10)	(2.50)	(1.24)	(1.41)	(2.27)	(4.23)	(2.81)
	H-L	0.357**	0.180	0.183	0.275***		0.422**	0.183	0.183	0.224**	
		(2.70)	(0.91)	(1.38)	(2.01)		(3.17)#	(0.82)	(1.17)	(1.65)	
Panel B: Results for MA (50) Strategy											
PIN	Low	-0.348***	-0.218***	-0.181**	-0.225**	0.124	0.024	0.168***	0.257**	0.257*	0.234**
		(-3.26)	(-2.04)	(-1.38)	(-1.35)	(0.98)	(0.17)	(1.94)	(1.98)	(1.36)	(1.85)
	2	-0.337***	-0.139*	-0.149	0.107	0.444***	0.050	0.344***	0.344***	0.707***	0.657***
		(-2.83)	(-1.11)	(-1.02)	(0.62)	(3.38)##	(0.34)	(2.55)	(2.46)	(4.47)	(5.15)###
	3	-0.211*	-0.127	-0.082	0.018	0.229***	0.159	0.330	0.452**	0.688***	0.530***
		(-1.72)	(-0.88)	(-0.49)	(0.09)	(1.97)	(1.03)	(1.63)	(2.23)	(3.97)	(3.92)##
	High	-0.102	-0.036	-0.038	0.177*	0.279***	0.306**	0.426*	0.463**	0.691***	0.385***
		(-0.80)	(-0.22)	(-0.24)	(1.14)	(2.75)##	(2.15)	(2.13)	(2.68)	(3.96)	(2.82)
	H-L	0.247***	0.182	0.143*	0.402***		0.283***	0.258	0.206	0.434***	
		(2.98)##	(1.41)	(1.36)	(3.98)###		(3.31)#	(1.32)	(1.68)	(4.38)##	

7.2. Support and resistance

The buying signal of a support-and-resistance strategy occurs when the price exceeds the recent n-day maximum by x percent, and the selling signal occurs when the price is below the n-day minimum price by x percent. We choose $x = 0.1, 0.5, 1$ and $n = 5, 10, 20$ to implement the strategy on the highest and lowest decile PIN portfolios and present the results in Table 19. Similar to the results of filter strategies, most of the high-minus-low portfolios yield positive difference returns and alphas, and many pass the Stepwise SPA tests. Again, the negative difference returns contribute to the high-minus-low differences substantially. significantly positive difference returns and alphas are commonly seen for the equally-weighted high-PIN portfolio but are rare for the value-weighted portfolio.

Table 18
Filter Strategy. This table reports the performance of filter strategy, which signals buying (selling) when the price goes up (down) by a threshold x percent from the recent n-day minimum (maximum). For each strategy, it presents the difference returns $R^d_{j,m,L}$, their alphas for the six-factor model and t-values (in parentheses) for the highest and lowest PIN decile portfolios and their difference portfolios. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$						α_j					
	Thresh-	Equally-Weighted			Value-Weighted			Equally-Weighted			Value-Weighted		
Days	old	Low	High	H-L	Low	High	H-L	Low	High	H-L	Low	High	H-L
10	1%	-0.367 **	0.449 ***	0.816 ***	-0.553 ***	0.130	0.684 ***	0.049	0.775 ***	0.725 ***	-0.130	0.526 ***	0.656 ***
		(-2.12)	(3.05)	(5.51) ###	(-3.56)	(0.73)	(4.02) ###	(0.24)	(5.74)	(4.36) ###	(-0.62)	(2.90)	(3.76) ###
	2%	-0.307 ***	0.420 ***	0.728 ***	-0.451 ***	-0.105	0.346 ***	0.029	0.756 ***	0.727 ***	-0.062	0.338 ***	0.400 ***
		(-2.22)	(3.16)	(5.14) ###	(-3.55)	(-0.65)	(2.06) #	(0.27)	(5.65)	(4.57) ###	(-0.35)	(3.25)	(2.34) ##
	5%	-0.225 **	-0.010	0.215 *	-0.445 ***	-0.068	0.377 ***	0.068	0.253 **	0.185	-0.056	0.287 ***	0.343 ***
		(-1.55)	(-0.07)	(1.40)	(-3.27)	(-0.37)	(1.76) #	(0.49)	(1.85)	(1.03)	(-0.31)	(1.99)	(1.56)
20	1%	-0.215 *	0.409 ***	0.625 ***	-0.461 ***	0.189	0.650 ***	0.194	0.728 ***	0.534 ***	-0.029	0.535 **	0.565 ***
		(-1.39)	(2.95)	(4.05) ###	(-3.08)	(0.78)	(2.67) ###	(1.10)	(5.80)	(3.00) ###	(-0.14)	(2.04)	(2.14) ##
	2%	-0.269 **	0.432 ***	0.701 ***	-0.377 ***	-0.020	0.358 *	0.087	0.796 ***	0.709 ***	0.014	0.387 ***	0.373 ***
		(-1.76)	(2.99)	(4.85) ###	(-2.65)	(-0.10)	(1.82) #	(0.72)	(5.53)	(4.28) ###	(0.08)	(2.84)	(1.96) #
	5%	-0.256 **	0.030	0.285 ***	-0.450 ***	-0.034	0.416 **	0.064	0.285 ***	0.222 *	-0.068	0.300 **	0.368 ***
		(-1.68)	(0.26)	(2.25) ##	(-3.89)	(-0.17)	(2.05) #	(0.43)	(2.44)	(1.31)	(-0.49)	(1.68)	(2.05) #
50	1%	-0.204 *	0.200 **	0.405 ***	-0.515 ***	0.183 *	0.698 ***	0.194 *	0.460 ***	0.266 **	-0.071	0.630 ***	0.702 ***
		(-1.30)	(1.59)	(2.89) ###	(-3.48)	(0.78)	(3.30) ###	(1.36)	(3.74)	(1.79)	(-0.38)	(3.03)	(2.80) ###
	2%	-0.346 ***	0.297 ***	0.643 ***	-0.350 ***	0.225 **	0.575 ***	-0.017	0.576 ***	0.593 ***	0.101	0.647 ***	0.547 ***
		(-2.57)	(2.33)	(4.66) ###	(-2.59)	(1.06)	(2.83) ###	(-0.12)	(4.00)	(2.96) ###	(0.54)	(3.79)	(2.22) ##
	5%	-0.274 ***	0.039	0.313 ***	-0.442 ***	0.084	0.526 ***	-0.027	0.305 ***	0.332 ***	-0.081	0.500 ***	0.582 ***
		(-2.39)	(0.37)	(2.74) ###	(-3.55)	(0.34)	(2.03) #	(-0.24)	(2.50)	(2.07) #	(-0.44)	(2.53)	(2.37) ##

Table 19
Support and Resistance Strategy. This table reports the performance of support-and-resistance strategy, which signals buying (selling) when the price is above (below) the recent n-day maximum (minimum) by a threshold x percent. For each strategy, it presents the difference returns $R^d_{j,m,L}$, their alphas for the six-factor model and t-values (in parentheses) for the highest and lowest PIN decile portfolios and their difference portfolios. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$						α_j					
	Thresh-	Equally-Weighted			Value-Weighted			Equally-Weighted			Value-Weighted		
Days	old	Low	High	H-L	Low	High	H-L	Low	High	H-L	Low	High	H-L
5	0.1%	-0.587 **	0.232 ***	0.819 ***	-0.851 ***	-0.327	0.524 ***	-0.206 **	0.578 ***	0.784 ***	-0.517 ***	0.004	0.521 **
		(-2.12)	(3.05)	(5.51) ###	(-3.56)	(0.73)	(4.02) ###	(-1.49)	(4.07)	(4.71) ###	(-5.37)	(0.01)	(1.92) #
	0.5%	-0.701 ***	0.176 ***	0.877 ***	-0.976 ***	-0.333	0.643 ***	-0.329 ***	0.519 ***	0.848 ***	-0.639 ***	0.058	0.697 ***
		(-2.22)	(3.16)	(5.14) ###	(-3.55)	(-0.65)	(2.06) #	(-2.47)	(3.64)	(5.02) ###	(-6.19)	(0.25)	(2.93) ###
	1.0%	-0.614 **	-0.124	0.490 *	-0.922 ***	-0.510	0.412 ***	-0.199 **	0.250 ***	0.449 ***	-0.523 ***	-0.115	0.408 ***
		(-1.55)	(-0.07)	(1.40) #	(-3.27)	(-0.37)	(1.76) #	(-1.59)	(1.87)	(2.63) ###	(-5.15)	(-0.61)	(2.14) ##
10	0.1%	-0.522 *	0.109 ***	0.631 ***	-0.836 ***	-0.439	0.397 ***	-0.088	0.480 ***	0.569 ***	-0.463 ***	-0.009	0.454 **
		(-1.39)	(2.95)	(4.05) ###	(-3.08)	(0.78)	(2.67) ##	(-0.76)	(3.15)	(3.76) ###	(-4.02)	(-0.03)	(2.05) ##
	0.5%	-0.408 **	-0.017 ***	0.391 ***	-0.817 ***	-0.364	0.453 *	0.011	0.360 ***	0.349 ***	-0.443 ***	0.134	0.577 ***
		(-1.76)	(2.99)	(4.85) ###	(-2.65)	(-0.10)	(1.82) #	(0.08)	(2.43)	(2.16) ##	(-3.95)	(0.58)	(3.41) ###
	1.0%	-0.496 **	-0.199	0.297 ***	-0.876 ***	-0.404	0.472 **	-0.013	0.244 **	0.258 **	-0.460 ***	0.094	0.554 ***
		(-1.68)	(0.26)	(2.25) #	(-3.89)	(-0.17)	(2.05) #	(-0.11)	(1.47)	(1.34)	(-4.91)	(0.45)	(3.28) ###
20	0.1%	-0.428 *	0.040 **	0.468 ***	-0.752 ***	-0.238 *	0.514 ***	-0.005	0.394 ***	0.398 ***	-0.352 ***	0.191 *	0.544 ***
		(-1.30)	(1.59)	(2.89) ###	(-3.48)	(0.78)	(3.30) ###	(-0.04)	(2.82)	(2.41) ##	(-3.66)	(0.81)	(2.39) ##
	0.5%	-0.397 ***	-0.082 ***	0.315 ***	-0.682 ***	-0.359 **	0.323 ***	0.044	0.264 ***	0.220 *	-0.279 ***	0.062	0.340 **
		(-2.57)	(2.33)	(4.66) ###	(-2.59)	(1.06)	(2.83) ###	(0.43)	(1.86)	(1.29)	(-2.89)	(0.24)	(1.37)
	1.0%	-0.548 ***	-0.339	0.209 ***	-0.675 ***	-0.317	0.358 ***	-0.081	0.071	0.153	-0.303 ***	0.109	0.411 ***
		(-2.39)	(0.37)	(2.74) ##	(-3.55)	(0.34)	(2.03) #	(-0.77)	(0.43)	(0.80)	(-3.61)	(0.46)	(1.90) #

7.3. Channel breakout

A c percent channel occurs when the maximum over the previous n days is not higher than the minimum by c percent. The channel breakout rule involves buying when the price goes up by x percent from the recent n-day minimum and selling when the price does down by x percent from the recent n-day maximum. Table 20 reports the results of implementing the channel breakout strategy on the highest and lowest decile PIN portfolios with channel width equal to $c = 1, 2, 3$ percent, breakout threshold equal to $x = 0.5, 1$ percent, and $n = 5, 10, 15$ days.

Similar to what is found in support-and-resistance strategies, the lowest decile PIN portfolios perform poorly in channel breakout strategies with negative difference returns throughout. The difference is that channel breakout strategies do not work for the highest PIN portfolios either, especially for the equally-weighted portfolio. As a result, there is no consistent pattern for the high-minus-low difference returns. In terms of alphas, there are fewer significant results for both highest and the lowest portfolios, and again, there is no consistent patterns for the high-minus-low alphas of the equally-weighted portfolios. However, there are some positive alphas for the value-weighted portfolios. To sum up, the investigations on three alternative technical trading rules reveal that, while high-PIN portfolios perform better than the low-PIN portfolios in the filter and support-and-resistance strategies, neither of the portfolios do well in the channel breakout strategies.

Table 20

Channel Breakout Strategy. This table reports the performance of channel breakout strategy. A c percent channel occurs when the maximum over the previous n days is not higher than the minimum by c percent, and the strategy which signals buying (selling) when the price is above (below) the channel by a threshold x percent. For each strategy, it presents the difference returns $R^d_{j,m,L}$, their alphas for the six-factor model and t-values (in parentheses) for the highest and lowest PIN decile portfolios and their difference portfolios. One, two or three asterisks (*) or hashes (#) denote significance at the 0.1, 0.05, and 0.01 levels, respectively. Asterisks are used for the single hypothesis testing and hashes are used for the Stepwise SPA testing.

		$R^d_{j,m,L}$						α_j					
	Channel	Equally-Weighted			Value-Weighted			Equally-Weighted			Value-Weighted		
Days	Width	Low	High	H-L	Low	High	H-L	Low	High	H-L	Low	High	H-L
Panel A: Threshold=0.5%													
5	1%	-0.561 ***	-0.405 ***	0.156 ***	-0.587 ***	0.010 ***	0.596 ***	-0.301 ***	-0.114	0.188 **	-0.159	0.256 *	0.415 **
		(-4.12)	(-2.23)	(0.87)	(-4.21)	(0.03)	(2.18) #	(-2.18)	(-0.67)	(1.01)	(-1.07)	(1.04)	(1.31)
	2%	-0.425 ***	-0.028 ***	0.398 ***	-0.369 ***	-0.125 ***	0.244 ***	0.050	0.370 ***	0.321 ***	0.062	0.168 *	0.106
		(-3.21)	(-0.16)	(2.11) #	(-2.87)	(-0.59)	(1.36)	(0.32)	(2.09)	(1.69)	(0.62)	(0.91)	(0.54)
	3%	-0.270 ***	-0.183 ***	0.087 ***	-0.349 ***	-0.188 ***	0.161 ***	0.112	0.231 *	0.120	0.049	0.100	0.051
		(-1.70)	(-1.16)	(0.53)	(-2.72)	(-0.94)	(0.75)	(0.78)	(1.31)	(0.65)	(0.50)	(0.52)	(0.22)
10	1%	-0.221 ***	-0.756 ***	-0.535 ***	-0.333 ***	-0.245 ***	0.089 ***	-0.102	-0.444 **	-0.342 *	-0.144 **	0.116	0.260 **
		(-1.35)	(-3.24)	(-2.49)	(-2.21)	(-1.02)	(0.41)	(-0.66)	(-1.92)	(-1.28)	(-1.36)	(0.55)	(1.33)
	2%	-0.644 ***	-0.315 ***	0.329 ***	-0.529 ***	-0.056 ***	0.473 ***	-0.227 **	0.118	0.345 **	-0.080	0.296 **	0.376 ***
		(-4.06)	(-1.53)	(1.30)	(-4.17)	(-0.21)	(1.88)	(-1.36)	(0.54)	(1.15)	(-0.57)	(1.43)	(1.71)
	3%	-0.553 ***	-0.396 ***	0.157 ***	-0.213 ***	0.106 ***	0.318 ***	-0.125	-0.144	-0.018	0.160 ***	0.461 ***	0.301 **
		(-3.34)	(-1.61)	(0.55)	(-1.71)	(0.40)	(1.23)	(-0.78)	(-0.49)	(-0.05)	(1.52)	(2.08)	(1.12)
15	1%	-0.574 ***	-0.839 ***	-0.264 ***	-0.514 ***	-0.529 ***	-0.016 ***	-0.186	-0.599 ***	-0.413	-0.175 **	-0.076	0.099
		(-3.04)	(-3.68)	(-1.04)	(-3.10)	(-2.77)	(-0.07)	(-1.35)	(-2.27)	(-1.15)	(-1.24)	(-0.36)	(0.39)
	2%	-0.607 ***	-0.772 ***	-0.165 ***	-0.209 ***	0.039 ***	0.248 ***	-0.269 *	-0.248	0.021	0.035	0.291 **	0.255 **
		(-4.43)	(-2.98)	(-0.69)	(-1.50)	(0.14)	(0.88)	(-1.75)	(-1.04)	(0.07)	(0.25)	(1.33)	(1.05)
	3%	-0.391 ***	-0.470 ***	-0.079 ***	-0.359 ***	0.022 ***	0.381 ***	-0.083	-0.137	-0.055	-0.082	0.392 ***	0.474 ***
		(-2.24)	(-1.86)	(-0.26)	(-2.89)	(0.11)	(2.20) #	(-0.49)	(-0.43)	(-0.13)	(-0.75)	(1.75)	(1.76)

		$R^d_{j,m,L}$						α_j					
	Channel	Equally-Weighted			Value-Weighted			Equally-Weighted			Value-Weighted		
Days	Width	Low	High	H-L	Low	High	H-L	Low	High	H-L	Low	High	H-L
Panel B: Threshold=1%													
5	1%	-0.473 ***	-0.680 ***	-0.207 ***	-0.436 ***	-0.196 ***	0.240 ***	-0.270 ***	-0.073	0.197 *	-0.036	-0.004	0.032
		(-4.55)	(-2.92)	(-0.91)	(-3.31)	(-0.72)	(0.98)	(-2.80)	(-0.39)	(0.90)	(-0.30)	(-0.01)	(0.15)
	2%	-0.431 ***	-0.434 ***	-0.003 ***	-0.537 ***	-0.258 ***	0.279 ***	0.009	-0.193	-0.202	-0.097 *	0.239 **	0.336 **
		(-3.14)	(-1.73)	(-0.00)	(-3.92)	(-1.17)	(1.45)	(0.06)	(-0.69)	(-0.77)	(-0.92)	(1.11)	(1.80)
	3%	-0.439 ***	-0.014 ***	0.426 ***	-0.429 ***	-0.055 ***	0.374 ***	0.082 *	0.371 ***	0.288 ***	-0.038	0.354 ***	0.392 ***
		(-2.73)	(-0.08)	(2.34) ##	(-2.66)	(-0.24)	(1.60)	(0.70)	(2.02)	(1.81)	(-0.34)	(2.01)	(2.01)
0	1%	-0.505 ***	-1.121 ***	-0.617 ***	-0.207 ***	-0.298 ***	-0.091 ***	-0.140 *	-0.954 ***	-0.813 ***	0.204 ***	0.189 *	-0.016
		(-2.70)	(-4.08)	(-2.30)	(-1.30)	(-1.15)	(-0.35)	(-1.10)	(-3.91)	(-3.03)	(2.00)	(0.87)	(-0.05)
	2%	-0.339 ***	-0.599 ***	-0.260 ***	-0.433 ***	-0.293 ***	0.140 ***	0.238 ***	-0.369 ***	-0.607 ***	0.003	-0.035	-0.038
		(-2.02)	(-2.61)	(-1.13)	(-2.96)	(-1.89)	(0.85)	(2.34)	(-1.80)	(-2.74)	(0.02)	(-0.24)	(-0.18)
	3%	-0.621 ***	-0.485 ***	0.135 ***	-0.417 ***	0.041 ***	0.458 ***	-0.190	0.077	0.266	-0.111	0.201 **	0.312 **
		(-3.73)	(-2.08)	(0.49)	(-2.75)	(0.15)	(1.76)	(-1.10)	(0.34)	(0.83)	(-1.02)	(0.97)	(1.44)
5	1%	-0.767 ***	-1.224 ***	-0.457 ***	-0.673 ***	-0.370 ***	0.304 ***	-0.140	-0.751 ***	-0.611 ***	-0.143 *	0.367 ***	0.511 ***
		(-3.87)	(-4.80)	(-2.22)	(-3.73)	(-1.41)	(1.21)	(-1.39)	(-3.86)	(-2.89)	(-1.11)	(1.88)	(2.50)
	2%	-0.511 ***	-0.751 ***	-0.240 ***	-0.443 ***	-0.098 ***	0.345 ***	-0.071	-0.179	-0.109	0.073	0.288 **	0.216
		(-3.79)	(-3.19)	(-0.93)	(-2.80)	(-0.34)	(1.23)	(-0.51)	(-0.83)	(-0.42)	(0.68)	(1.34)	(0.83)
	3%	-0.678 ***	-0.650 ***	0.028 ***	-0.311 ***	-0.229 ***	0.083 ***	-0.256 **	-0.342	-0.086	0.028	0.158	0.130
		(-3.94)	(-2.73)	(0.11)	(-2.37)	(-1.12)	(0.47)	(-1.74)	(-1.23)	(-0.23)	(0.22)	(0.83)	(0.76)

8. Conclusions

This study examines the implications of the models of Wang (1993) and Blume et al. (1994) and offers strong evidence that securities with more private information proxied by PIN produce higher returns under an MA strategy than a buy-and-hold strategy. This result holds when the Fama and French (2015) five-factor model with an additional momentum factor is considered. This is also the case when we use varying MA lengths and equally or value-weighted portfolio returns; replace PIN with PIN_B, PIN_G, and Adjusted to form portfolios; and delay trades to the next day to implement the strategies. The difference returns remain positive for high-PIN portfolios even after accounting for firm size, volatility, and liquidity.

This study focuses on the moving average strategy, one of the most rudimentary tools adopted to perform technical analysis. Although three additional technical rules have also been examined, extending our research to other tools in details would be worthwhile. In addition, we conduct a cross-sectional investigation to determine which types of securities produce higher returns in a technical analysis. It would be interesting to conduct time-series analysis to determine whether technical analysis is more beneficial during the time when the level of information asymmetry is high. Further studies can shed more light on the sources of profitability from technical trading.

CRediT authorship contribution statement

Chiayu Hung: Software, Writing – original draft, Formal analysis. **Hung-Neng Lai:** Conceptualization, Methodology, Software, Formal analysis, Resources, Writing – review & editing, Visualization, Project administration, Funding acquisition.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets* 5 (1), 31–56.

Aslan, H., Easley, D., Hvidkjaer, S., O'Hara, M., 2011. The characteristics and informed trading: implications for asset pricing. *Journal of Empirical Finance* 18 (5), 782–801.
Avramov, D., Kaplanski, G., Subrahmanyam, A., 2021. Moving average distance as a predictor of equity returns. *Review of Financial Economics* 39 (2), 127–145.
Bai, J., Philippon, T., Savov, A., 2016. Have financial markets become more informative? *J Financ Econ* 122 (3), 625–654.
Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. *J Financ Econ* 49, 307–343.
Bessembinder, H., Chan, K., 1998. Market efficiency and the returns to technical analysis. *Financ Manage* 27 (2), 5–17.
Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy* 100 (5), 992–1026.
Blume, L., Easley, D., O'Hara, M., 1994. Market statistics and technical analysis: the role of volume. *Journal of Finance* 49 (1), 153–181.
Bodie, Z., Kane, A., Marcus, A.J., 2021. Investments, twelfth McGraw-Hill, New York.
Brennan, M.J., Huh, S.-W., Subrahmanyam, A., 2016. Asymmetric effects of infrmed trading on the cost of equity capital. *Manage Sci* 62 (9), 2460–2480.
Brock, W., Lakonishok, J., LeBaron, B., 1992. Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance* 47 (5), 1731–1764.
Brown, D.P., Jennings, R.H., 1989. On technical analysis. *Review of Financial Studies* 2 (4), 527–551.
Cespa, G., Vives, X., 2011. Dynamic trading and asset prices: Keynes vs. Hayek. *Review of Economic Studies* 79 (2), 539–580.
Chordia, T., Goyal, A., Saretto, A., 2020. Anomalies and false rejections. *Review of Financial Studies* 33 (5), 2134–2179.
Cochrane, J.H., 2011. Presidential address: discount rates. *Journal of Finance* 66 (4), 1047–1108.
Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under and overreactions. *Journal of Finance* 53 (6), 1839–1885.
De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98 (4), 703–738.
De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Positive feedback investment strategies and destabilizing rational speculation. *Journal of Finance* 45 (2), 379–395.
Detzel, A., Liu, H., Strauss, J., Zhou, G., Zhu, Y., 2021. Learning and predictability via technical analysis: evidence from bitcoin and stocks with hard-to-value fundamentals. *Financ Manage* 50 (1), 107–137.
Duarte, J., Young, L., 2009. Why is PIN priced? *J Financ Econ* 91, 119–138.
Easley, D., Hvidkjaer, S., O'Hara, M., 2002. Is information risk a determinant of asset returns? *Journal of Finance* 57 (5), 2185–2221.
Easley, D., Kiefer, N.M., O'Hara, M., 1997. The information content of the trading process. *Journal of Empirical Finance* 4, 159–186.
Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J.B., 1996. Liquidity, information, and infrequently traded stocks. *Journal of Finance* 51 (4), 1405–1435.
Fama, E.F., 1970. Efficient capital markets:a review of theory and empirical work. *Journal of Finance* 25 (2), 383–417.
Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. *J Financ Econ* 116 (1), 1–22.
Flugum, R., 2021. The trend is an analyst's friend: analyst recommendations and market technicals. *Financial Review* 56 (2), 301–330.
Friesen, G.C., Weller, P.A., Dunham, L.M., 2009. Price trends and patterns in technical analysis: atheoretical and empirical examination. *Journal of Banking and Finance* 33 (6), 1089–1100.
Garleanu, N., Pedersen, L.H., 2003. Adverse selection and the required return. *Review of Financial Studies* 17 (3), 643–665.
Grossman, S.J., Stiglitz, J.E., 1980. On the impossibility of informationally efficient markets. *American Economic Review* 70 (3), 393–407.
Grundy, B.D., Martin, J.S., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial Studies* 14 (1), 29–78.
Grundy, B.D., McNichols, M., 1989. Adverse selection and the required return. *Review of Financial Studies* 2 (4), 495–526.
Han, Y., Yang, K., Zhou, G., 2013. A new anomaly: the cross-sectional profitability of technical analysis. *Journal of Financial and Quantitative Analysis* 48 (5), 1433–1461.
Han, Y., Zhou, G., Zhu, Y., 2016. A trend factor: any economic gains from using information over investment horizons? *J Financ Econ* 122 (2), 352–375.
Hansen, P.R., 2005. A test for superior predictive ability. *Journal of Business and Economic Statistics* 23 (4), 365–380.
Harvey, C.R., Liu, Y., Zhu, H., 2015. …And the cross-Section of expected returns. *Review of Financial Studies* 29 (1), 5–68.
Hellwig, M.F., 1980. On the aggregation of information in competitive markets. *J Econ Theory* 22, 477–498.
Hong, H., Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54 (6), 2143–2184.
Hsu, P.-H., Hsu, Y.-C., Kuan, C.-M., 2010. Testing the predictive ability of technical analysis using a new stepwise test without data snooping bias. *Journal of Empirical Finance* 17 (3), 471–484.
Hsu, P.-H., Kuan, C.-M., 2005. Reexamining the profitability of technical analysis with data snooping checks. *Journal Of Financial Econometrics* 3 (4), 606–628.
Hsu, P.-H., Taylor, M.P., Wang, Z., 2016. Technical trading: is it still beating the foreign exchange market? *J Int Econ* 102, 188–208.
Johnson, T.C., 2002. Rational momentum effects. *Journal of Finance* 57 (2), 585–608.
Kavajecz, K.A., Odders-White, E.R., 2004. Technical analysis and liquidity provision. *Review of Financial Studies* 17 (4), 1043–1071.
Keim, D.B., Madhavan, A., 1997. Transactions costs and investment style: an inter-exchange analysis of institutional equity trades. *J Financ Econ* 46, 265–292.
Lee, C.M.C., Ready, M.J., 1991. Inferring trade direction from intraday data. *Journal of Finance* 46 (2), 733–746.
Lin, H.-W.W., Ke, W.-C., 2011. A computing bias in estimating the probability of informed trading. *Journal of Financial Markets* 14 (4), 625–640.
Lo, A.W., Hasanhodzic, J., 2009. The heretics of finance : Conversations with leading practitioners of technical analysis. Bloomberg Press, New York.
Lo, A.W., Mamaysky, H., Wang, J., 2000. Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation. *Journal of Finance* 55 (4), 1705–1765.
Lucas, R.E., 1978. Asset prices in an exchange economy. *Econometrica* 46 (6), 1429–1445.
Marshall, B.R., Cahan, R.H., Cahan, J.M., 2008. Can commodity futures be profitably traded with quantitative market timing strategies? *Journal of Banking and Finance* 32 (9), 1810–1819.
Marshall, B.R., Cahan, R.H., Cahan, J.M., 2008. Does intraday technical analysis in the us equity market have value? *Journal of Empirical Finance* 15 (2), 199–210.
Marshall, B.R., Nguyen, N.H., Visaltanachoti, N., 2017. Time series momentum and moving average trading rules. *Quantitative Finance* 17 (3), 405–421.
Menkhoff, L., 2010. The use of technical analysis by fund managers: international evidence. *Journal of Banking and Finance* 34 (11), 2573–2586.
Menkhoff, L., Taylor, M.P., 2007. The obstinate passion of foreign exchange professionals: technical analysis. *J Econ Lit* 45 (4), 936–972.
Moskowitz, T.J., Ooi, Y.H., Pedersen, L.H., 2012. Time series momentum. *J Financ Econ* 104 (2), 228–250. Special Issue on Investor Sentiment
Neely, C.J., Rapach, D.E., Tu, J., Zhou, G., 2014. Forecasting the equity risk premium: the role of technical indicators. *Manage Sci* 60 (7), 1772–1791.
Newey, W., West, K., 1987. A simple positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55, 703–708.
Novy-Marx, R., Velikov, M., 2016. A taxonomy of anomalies and their trading costs. *Review of Financial Studies* 29 (1), 104–147.
Osler, C., 2003. Currency orders and exchange rate dynamics: an explanation for the predictive success of technical analysis. *Journal of Finance* 58 (5), 1791–1819.
Park, C.-H., Irwin, S.H., 2007. What do we know about the profitability of technical analysis? *J Econ Surv* 21 (4), 786–826.
Pastor, Ľ., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. *Journal of Politial Economy* 11, 642–685.
Politis, D.N., Romano, J.P., 1994. The stationary bootstrap. *J Am Stat Assoc* 89 (428), 1303–1313.
Ready, M.J., 2002. Profits from technical trading rules. *Financ Manage* 31 (3), 43–61.
Samuelson, P.A., 1965. Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review* 6 (2), 41–49.
Shleifer, A., Vishny, R.W., 1997. The limits of arbitrage. *Journal of Finance* 52 (1), 35–55.
Shynkevich, A., 2012. Performance of technical analysis in growth and small cap segments of the us equity market. *Journal of Banking and Finance* 36 (1), 193–208.
Shynkevich, A., 2012. Short-term predictability of equity returns along two style dimensions. *Journal of Empirical Finance* 19 (5), 675–685.
Shynkevich, A., 2016. Predictability in bond returns using technical trading rules. *Journal of Banking and Finance* 70, 55–69.
Shynkevich, A., 2017. Two tales of return predictability: the case of asia-pacific equity markets. *J Forecast* 36 (3), 257–272.
Smith, D.M., Wang, N., Wang, Y., Zychowicz, E.J., 2016. Sentiment and the effectiveness of technical analysis: evidence from the hedge fund industry. *Journal of Financial and Quantitative Analysis* 51 (6), 1991–2013.
Sullivan, R., Timmermann, A., White, H., 1999. Data-snooping, technical trading rule performance, and the bootstrap. *Journal of Finance* 54 (5), 1647–1691.
Vayanos, D., Wang, J., 2011. Liquidity and asset returns under asymmetric information and imperfect competition. *Review of Financial Studies* 25 (5), 1339–1365.
Wang, J., 1993. A model of intertemporal asset prices under asymmetric information. *Review of Economic Studies* 60 (2), 249–282.
Watanabe, M., 2008. Price volatility and investor behavior in an overlapping generations model with information asymmetry. *Journal of Finance* 63 (1), 229–272.
White, H., 2000. A reality check for data snooping. *Econometrica* 68 (5), 1097–1126.
Yan, Y., Zhang, S., 2012. An improved estimation method and empirical properties of the probability of informed trading. *Journal of Banking and Finance* 36 (2), 454–467.
Zakamulin, V., Giner, J., 2020. Trend following with momentum versus moving averages: a tale of differences. *Quantitative Finance* 20 (6), 985–1007.
Zhu, Y., Zhou, G., 2009. Technical analysis: an asset allocation perspective on the use of moving averages. *J Financ Econ* 92 (3), 519–544.