Market Signal to Managers: Effect of Investors' Private Information on Earnings Management

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Abstract

We study the interactions between financial markets and the real economy, focusing on the effect of investors' private information on earnings management. We use single-level and multi-level regression models, along with the probability of informed trading (PIN), the dynamic measure for the probability of informed trading (DPIN), and the dynamic measure of the probability of informed trading with size effects (SDPIN) to assess private information. We find that managers are less likely to engage in earnings manipulation when stock prices reflect more private information from outside investors. Furthermore, we show that private information has a stronger impact on upward earnings management. Our findings suggest that stock price movements align with the hypotheses of managerial learning, incentive channels, and the flow of information from secondary markets to economic sectors.

Keywords: Secondary Market, Informed Trading, Private Information, Size Order Effect, Earnings Management.

JEL Classification: C49; G14; G19

Highlights

- We introduce a new measure of private information considering trade size and volume
- There is negative relationship between earnings management and private information
- There is stronger response to private information in managers who inflate earnings
- Firm-specific characteristics primarily drive variations in earnings management

1. Introduction

There is extensive literature studying the one-way effect of the economy on the stock market (see e.g., Jiang et al., 2021; Loureiro and Silva, 2022; Wang et al., 2024), which assumes that insiders (managers) possess complete information about the firm and that stock prices reflect investors' expectations about the firm's ability to generate future cash flows. Therefore, the only way stock markets influence the economy is through stock trade liquidity, as it can negatively impact the cost of capital, especially during initial public offerings (Bond et al., 2012). However, the notion of financial markets as a mere sideshow is debated, since the evolution of stock prices also affects the economy. Previous studies outline a two-stage mechanism through which financial markets influence the economy: one involves generating knowledge that drives price movements, and another considers managerial reactions to these movements (Glosten and Milgrom, 1985; Kyle, 1985).

There are both theoretical and empirical studies on how the feedback effects of financial markets influence managerial decisions and, consequently, the economy. For example, Boot and Thakor (1997) use feedback effects to explain firms' choice to issue publicly traded securities instead of seeking private financing, Luo (2005) finds that decision-makers may learn from prices when evaluating merger opportunities, Bakke and Whited (2010) show that the sensitivity of investment to price is greater when more confidential news is embedded in the stock price, and Durnev et al. (2004) reveals that price informativeness is positively related to the effectiveness of investment.

Another strand of literature examines the impact of financial markets on firm value, management forecasts, discretionary disclosure, CEO compensation, and board dependence (see, e.g., Kang and Liu, 2008; Bharath et al., 2013; and Zuo, 2016). Rappaport (1987) argues that managers should not worry about what the stock market says but, instead, learn what the stock price reveals about investors' expectations regarding firm performance. They also show how managers can "read" market expectations about hurdle rates and are guided by the market via the payment price, concluding that financial markets can have a feedback effect on the economy. In general, evidence suggests that managers are better positioned to evaluate operational and financial restructuring options for their firms if they carefully interpret market signals (Bond et al., 2010; Peress, 2014; Sletten, 2012). However, the mechanisms through which the stock market infuences the economy are not yet fully understood. This paper aims to identify such mechanisms.

Edmans et al. (2017) suggest that the effect of stock prices on firms' decisions depends not on the total information embedded in the stock price, known as forecasting price efficiency (FPE), but on the proportion of information that is not yet known by the manager, called revelatory price efficiency (RPE).[2] However, because there is not a reliable proxy for RPE yet, studying this topic empirically

[2] Bond et al. (2000) and Edmans et al. (2017) argue that the impact of financial markets on the value of managerial decisions may not rely on the total information embedded in stock prices (FPE) because some of this information is already known to decision makers. Instead, it depends on how much information stock prices reveal to managers making those decisions. Bond et al. (2000) referred to this effect as revelatory price efficiency (RPE).

remains difficult. Additionally, each stock may contain different levels of private information due to varying information acquisition costs across industries (Grossman and Stiglitz, 1980), which are hard to measure. Our study aims to determine the proportion of the stock price driven by private information and its impact on firms' decisions (see, e.g., Bond et al., 2012). Moreover, we develop a new measure of private information, the SDPIN, which builds on the dynamic measure for the probability of informed trading (DPIN) by Change et al. (2014). This measure considers the size and volume of stock trades. Our goal is examine how aggregate stock market dynamics influence earnings management, specifically analyzing the impact of investors' private information on earnings management and whether managers incorporate this private information into their decisions.

We use single-level and multi-level regressions to evaluate the relationship mentioned earlier. Our study reveals the following findings. First, we show that the feedback effect is more singificant in firms whose stock prices are more heavily impacted by private information, which reduces earnings manipulation, so managers are less likely to engage in earnings management when stock prices contain more private information. Second, when analyzing upward and downward earnings management, we observe that although investors' private information can influence managers' decisions on firms' earnings in both scenarios, managers who have consistently inflated earnings respond more stronly to private information. Third, our results indicate that intrinsic firm characteristics mainly drive differences in earnings management, with industry-level variables also playing a significant role, although we find that investors' private information at the industry level does not sabstantially affect earnings management.

This paper makes several contributions to the literature. Firstly, it provides empirical evidence supporting the existence of information transmission from financial markets to the economy. This substantiates the idea that financial markets play a crucial role beyond being merely peripheral, demonstrating their potential for feedback effects on the economy. Secondly, it addresses a gap in the existing literature by exploring a new external factor that infuences managers' decisions on earnings management and corporate disclosure. In doing so, it expands the currently limited understanding of these key aspects of corporate behavior. Previous studies indicate that informed traders are attracted to less transparent firms, as opacity increases the profitability of private information acquisition (Brown and Hillegeist, 2007; Gao and Liang, 2013; Verrecchia, 1982). Tests by Zuo (2016) show similar results: smaller companies with limited analyst coverage and low institutional holdings experience more informed trading. As a result, managers in these firms, who have privately informed trading, are held accountable by investors if they ignore market reactions and continue to manipulate company accounting profits. Thirdly, our methodology differs from previous research by using a multi-level approach instead of simply employing dummy variables for firm sectors to analyze industry-level effects on earnings management. This allows for a more detailed examination of specific factors affecting earnings management, especially industry-level investors' private influence information.

Our findings are relevant to firms and financial market participants. We concluded that the feedback effect from informed trading improves firms' financial management efficiency by lowering discretionary accruals in accounting profits and encouraging more transparent corporate information disclosures. Additionally, the decrease in information asymmetry reduces investors' costs and the effort needed to search for information in proces independetly. While some may worry this could discourage informed investors, it is important to recognize that personal trading information includes both managers' confidential insights and investor-discovered information not yet unknown to companies. Moreover, speculators will continue seeking new private information as long as the benefits exceeds the costs of acquisition, especially when abnormal returns are at stake.

The remaining sections of the paper are organized as follows. Section 2 reviews the literature and develops the research hypotheses. Section 3 presents the data sample and methodology. Section 4 discusses our main findings and interpret the results. Section 5 concludes the paper.

2. Literature review

2.1. Investors' private information

Generating information is a remarkable ability of the financial markets. According to Roll (1988), it occurs through two mechanisms: one involves the frequent revaluations of information, such as the share price after the public disclosure of relevant information, such as the country's GDP and unemployment rate, the central bank's interest rate, and a firm's quarterly results- and the other involves stock trading. This private information can be reflected in stock prices through the trading of outside investors (Glosten and Milgrom, 1985; Kyle, 1985).

Different types of information are embedded in stock prices. For instance, the investors' private information held by investors in a stock price includes both public and private information, which may be "secret'" (unknown to managers), "not secret" (known by managers), or "partially secret" (partially known by managers). Managers make decisions based on the available information. If their decisions are influenced by stock price fluctuations, then we can say that the stock market impacts the economy. Bond et al. (2012) identify two main channels through which the stock market may influence managerial decisions: learning and incentives channels.[3]

In the learning channel, it is assumed that managers' decisions are affected by the investors' private information embedded in stock prices, but managers are unaware of this information. For instance, suppose that a manager has private information *A* investors have not yet learned, while outside investors possess private information *B* that managers are unaware of. According to conventional wisdom, information *A* has a greater impact on managerial decisions than information *B*, because it is known to the managers. However, Chen et al. (2007), argue that as long as information *B* exists,

[3] The concept of the learning channel dates back to Hayek (1945), who argued that the "price is a useful source of information". The market price is efficient and consists of information gathered from various sources. Decision-makers in the real world, who are unlikely to be fully informed, will want to learn from the price.

managers can learn from carefully observing stock price fluctuations if B is embedded in them. Subrahmanyam and Titman (1999) explain that during daily trading, traders may unintentionally discover valuable insights about firms that managers do not know. As a result, managers can learn about a firm's future prospects by monitoring the evolution of stock prices over time, which could lead to different management decisions than they would have made otherwise. The literature highlights several critical instances where private information affects managers' decisions, such as in evaluating mergers and acquisitions, investment projects, and earnings forecasts disclosure (Bakke and Whited, 2010; Foucault and Fresard, 2012; Luo, 2005; and Loureiro and Taboada, 2015). Moreover, Chen et al. (2007) demonstrate that stock prices contain information that managers do not possess and can learn from, and Zuo (2016) shows that investors' private information helps managers improve the accuracy of their earnings forecast.

In the incentives channel, managers do not gain new information from observing stock price fluctuations. Instead, incentives are influenced by the stock price because stock options are linkedto their employment contracts. This channel was first identified by Baumol (1965), with an early formalization by Fishman and Hagerty (1989). We observe that, however, the role of the stock price in these two channels is slightly different (Bond et al., 2011). While in the learning channel, the price reveals new information managers that they can consider in their decisions, in the incentives channel, the stock price influences the manager's motivation to take effective actions. Specifically, the more the stock price reflects the manager's decisions, the stronger the incentive for the manager to make optimal choices (Nagar et al., 2003).[4] Several reasons justify these incentive mechanisms. Executives care about short-term stock prices because of CEO compensation, bonuses, takeover threats, or reputation. Kang and Liu (2008) examine this mechanism, and their findings support the theory that CEO pay depends on the market price and is positively related to the informativeness of that price.

2.2. Earnings management

While Healy and Wahlen (1999) define earnings management as the use of subjective accounting estimates in financial statements or structuring transactions to alter financial reports by managers, Schipper (1989) describes earnings management managers interfering with the information disclosure process to gain private benefits. This tendency is driven by the belief that investors tend to focus on accounting profits than on cash flows. Graham et al. (2005) demonstrate that executives view earnings as the main metric for public disclosure and that optimistic analyst forecast about the firm's short-term profits help build credibility with market participants. The existing literature also indicates a positive relationship between earnings and stock returns (Chan et al., 2006; Demirtas and Zirek, 2011).

[4] For example, the manager's main goal is to maximize the firm's stock price. However, since the market cannot directly see the manager's decisions, stock prices do not fully reflect the expected future cash flows. For instance, it leads to underinvestment if investments that increase cash flows by $1 do not raise the share price by $1. When price efficiency improves, stock prices better reflect the firm's true value, including benefits from the manager's investments, which reduces underinvestment as stock prices more accurately align with the actual value created by the manager decisions.

Other studies, such as those by Ronen and Yaari (2010), argue that earnings management is not necessarily unethical, although it can be difficult to distinguish between earnings manipulation (viewed as fraud) and reconciling profit through firm revenues and expenses. Similarly, Fatemeh and Narjes (2013) contend that earnings management should not be confused with illegal manipulation of financial results aimed at distorting reality ("cooking the books"). Despite these different viewpoints, most of the literature considers earnings management as one form of manipulation.

The manipulation of earnings by firms has been extensively examined by the existing literature (Moardi et al., 2020; Park, 2017; Watts and Zimmerman, 1978). It mainly mainly on the subjective and self-interested aspects related to managers. The most common reasons for firms to manipulate earnings include attracting outside investments, increasing bonuses, applying for government grants, and conducting stock buybacks. Besides the firms and managers, who have a direct stake in earnings manipulation, other factors are also explored in the literature (see, e.g., Chen et al., 2007; Cheng and Warfield, 2005; Fakhfakh and Nasti, 2012; Fathi, 2013; Goh et al., 2013; Healy, 1985). Specifically, Charfeddine et al. (2013) and Watts and Jimmerman (1990) categorize these factors into two groups: incentive factors, such as a firm's debt, size, performance, and growth, and constraint factors, like the characteristics of the board of directors, ownership structure, and auditing quality. Regarding external influences, increasing attention is given to how investors' sentiment affects information disclosure policies and earnings management; for example, Hurwitz (2018) investigates the relationship between investors' sentiment and managers' biased behaviours in forecasting firm accounting performance. It demonstrates that, during periods of high sentiment, earnings estimates tend to be more optimistic, and vice-versa.[5] Simpson (2013) notes that firms use discretionary accruals to inflate earnings during times of predominantly optimistic sentiment but adopt more conservative disclosures during periods of negative of investor sentiment pessimism.

2.3. Hypotheses development

The examination of external factors influencing future earnings management is still notably limited. The concept of informational feedback from secondary stock markets to earnings management is relatively new within this body of literature. Regarding information flow, studies by Richard (2000), Dai et al. (2013), and Fatemeh and Narjes (2013) confirm the impact of information asymmetry on firm earnings management, although these studies focus only on Chinese and Iranian stock exchanges. Nevertheless, these articles assume that managers possess complete information about firms and, consequently, about secondary markets itself sideshow.

Additionally, the existing literature on the feedback effect of speculators' personal information tends to follow the managerial learning hypothesis, which assumes that managers can learn about their firms by observing stock prices. For instance, Chen et al. (2007) argue that some of the investors' private

[5] Their reasoning is that financial executives tend to overstate firm accounting profit by adjusting accruals in response to investors' sentiment, which affects the market's ability to price firm shares efficiently.

information embedded in a stock price might be new to the manager. Zuo (2016), following Chen et al. (2007), concludes that the learning channel helps managers improve earnings forecasts and that the presence of investors' private information can potentially lead to higher abnormal returns at the expense of insiders. This can deter managers from persistently inflating accruals and increases the likelihood that the truth will eventually come to light. Thus, when managers are aware of investors' private information, they are less likely to manipulate earnings.

Therefore, we hypothesize that: *There is a negative relationship between the investors' private information embedded in the stock price and managers' earnings management performance.*

3. Data sample and methodology

3.1. Data sample

Our data sample inlcudes quarterly stock price data for firms in the S&P 500 index.[6] Specifically, we gather data on 479 U.S. stocks listed on the NYSE and NASDAQ from January 2018 to December 2021. Table 1 offers more details about our data sample.

*****Insert Table 1 around here*****

3.2. Investors' private information measures

Our study builds on the work of Chen et al. (2007) and Zuo's (2016). We argue that informed investors' private information may include private information *B* (see section 2.1), which is new to managers and uninformed investors, and private information *C,* known only by managers (unknown to uninformed investors). Both types of information can influence insiders' decisions – information B through learning channel and information C through the incentives channel. Investors' private information is defined as the total amount of information *B* and *C*, - possibly known by managers (*C*) but entirely unknown to others (*B*).

We use three proxies for investors' private information: the probability of informed trading (PIN) developed by Easley et al. (2002), a dynamic measure for the probability of informed trading (DPIN) presented by Chang et al. (2014) and Chang and Wang (2015), and our newly developed measure called the probability of informed trading with size effects (SDPIN).

3.2.1. Probability of informed trading (PIN)

The PIN measure builds upon Easley et al.'s (2002) EHO PIN measure, incorporating improvements

[6] The S&P 500 is a stock market index that tracks the stock performance of 500 of the largest companies listed on U.S. stock exchanges. According to Standard and Poor's, the index accounts for about 80 percent of the total value of all stocks traded in the U.S. It includes stocks from 11 industry sectors, as defined by the Global Industry Classification Standard (GICS).

from Lee and Ready (1991), Ellis et al. (2000), Lin and Ke (2011), and Yan and Zhang (2012). The PIN measure is calculated as follows:

1. Classify the number of buy orders (B) and the number of sell orders (S) in a single trading day, using the Lee-Ready Algorithm and EMO algorithm to classify trades of stock listed on the NYSE exchange.

2. Estimate the likelihood function for a single trading day of a stock, using Lin and Ke (2011) and Yan and Zhang (2012) methods:

$$L(\theta|B_i, S_i) = Log[\alpha\delta e^{e_{1i}-e_{max\,i}} + \alpha(1-\delta)e^{e_{2i}-\varepsilon_{max\,i}} + (1-\alpha)e^{e_{3i}-e_{max\,i}}] + \\ + B_i \log(\varepsilon_b + \mu) + S_i \log(\varepsilon_s + \mu) - (\varepsilon_b + \varepsilon_s) + e_{maxi} - \log(S_i! B_i!) \quad (1)$$

where $e_{1i} = -\mu - B_i \log\left(1 + \frac{\mu}{\varepsilon_b}\right)$, $e_{2i} = -\mu - S_i \log\left(1 + \frac{\mu}{\varepsilon_s}\right)$, and $e_{3i} = -B_i \log\left(1 + \frac{\mu}{\varepsilon_s}\right) - S_i \log\left(1 + \frac{\mu}{\varepsilon_s}\right)$, $e_{maxi} = \max(e_{1i}, e_{2i}, e_{3i})$, δ is the probability of bad news, ε_b and ε_s are the daily arrival rates of noise traders that submit buy and sell orders, respectively; α is the probability that some traders acquire new (private) information about the firm fundamental, and μ is the arrival rate of informed traders, given the information or event occurs.

3. Using trading information over *J* days and assuming cross-trading-day independence to estimate *(ε_b, ε_s, α, μ)* by maximizing the following likelihood function:

$$V = L(\theta|B, S) = \prod_{j=1}^{j=J} L(\theta|B_j, S_j) \quad (2)$$

4. Then PIN is calculated as follows:

$$PIN = \frac{\alpha\mu}{\alpha\mu + \varepsilon_s + \varepsilon_b} \quad (3)$$

3.2.2. Dynamic probability of informed trading (DPIN)

DPIN is based on the model by Chang et al. (2014, 2015) to isolate the unexpected components of returns from the residual of the autoregressive model by Schwert (1990), modified by Jones et al. (1994) and Avramov et al. (2006). First, we classify the trade orders into sell orders and buy orders according to Lee and Ready's (1991) and Ellis et al.'s (2000) algorithms. Then unexpected components of returns are isolated as the residuals from the below regression:[7]

$$R_{i,j} = \gamma_0 + \sum_{k=1}^{5} \gamma_{1i,k} D_k^{day} + \sum_{k=1}^{26} \gamma_{2i,k} D_k^{Int} + \sum_{1}^{12} \gamma_{3i,k} R_{i,j-k} + \varepsilon_{i,j} \quad (4)$$

[7] Chang et al. (2014) follow Jones et al. (1994) and Avramov et al. (2006) in regressing the daily return of individual stocks on their own 12 lags (covering about two weeks) instead of on 22 lags (covering about one month) as in Schwert (1990) model. The DPIN is calculated for each 15-minute during the day, meaning its average is computed using 26 DPIN values perday.

where $R_{i,j}$ is the dependent variable and represents the return on stock i at the intraday interval j, with $j = 1, \dots, 26$; D_k^{Day} represents the day-of-week dummy variables, from Monday to Friday, and D^{Int} represents dummy variables corresponding to each 15-minute interval over the day t; $\varepsilon_{i,j}$ is a measure of the unexpected return.

A *buy* order that generates a negative (positive) unexpected return is classified as an informed (uninformed) trade, whereas a *sell* order with a positive (negative) unexpected return is classified as an informed (uninformed) trade. The DPIN measure is, therefore, constructed, as follows:

$$DPIN_{BASE_{i,j}} = \frac{NB_{i,j}}{NT_{i,j}}(\varepsilon_{i,j} < 0) + \frac{NS_{i,j}}{NT_{i,j}}(\varepsilon_{i,j} > 0) \quad (5)$$

where $NB_{i,j}$ and $NS_{i,j}$ are the number of *buy* and *sell* orders, respectively, and $NT_{i,j}$ is the total number of trades of stock i on day j.

3.2.3. Dynamic probability of informed trading with the size order effects (SDPIN)

Both PIN and DPIN measures distinguish informed trades from uninformed ones by assessing the likelihood that a trade is based on private information. Estimating the PIN measure with high-frequency trade data is time-consuming due to its complexity, a challenge that is worsened by the increasing popularity of high-frequency trading[8]. We also observe that estimating informed trading using daily or weekly data does not fully capture the information potentially linked to stock trades.

While the DPIN measure is easier to calculate, it only considers the number of trades and overlooks order sizes. Chang et al. (2014) recognised this limitation and introduced DPIN_SIZE and DPIN_SMALL to estimate private information based on large and small trade orders, respectively. However, these measures remain insufficient, as investors can strategically use different order sizes to hide informed trades. To overcome this, we propose a new dynamic intraday measure with size order effects (SDPIN), which accounts for both the number and size of informed trades. Our SDPIN measure built on the DPIN, enhancing it by also including trade order sizes (volume). The process is as follows: first, we use Lee and Ready's (1991) and Ellis et al.'s (2000) algorithms to classify orders; second, we isolate the unexpected component of returns (the residuals) from the following regression: [9]

$$R_{i,j} = \gamma_0 + \sum_{k=1}^{5} \gamma_{1i,k} D_k^{day} + \sum_{k=1}^{22} \gamma_{3i,k} R_{i,j-k} + \varepsilon_{i,j} \quad (6)$$

where $R_{i,j}$ is the stock i return on day k (j=1, …, 4), D_k^{Day} is the day-of-week dummy variable (from Monday to Friday).

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[8] Estimating PIN involves complex computations, including the likelihood function that accounts for various factors like the number of buy and sell orders. It also requires managing floating-point exceptions and boundary solutions (Lin and Ke, 2011; Yan and Zhang, 2012). Moreover, parameter estimation over multiple days demands substantial computational power and time due to the need to process a large volume of high-frequency data points, ensuring accuracy and statistical significance.

[9] We estimate SDPIN directly for each trading day by substituting the dummy variables for specific 15-minute intervals with dummy variables for each trading day of the week and incorporating 22 lags of daily returns.

To identify informed trades, we use the residual $\varepsilon_{i,j}$ as a proxy for unexpected returns. We classify buying trades as informed when there are negative unexpected returns and as uninformed when there are positive unexpected returns. Conversely, we classify selling trades as informed when there are positive unexpected returns and as uninformed when there are negative unexpected returns. The DPIN measure is constructed according to Equation (6).

The level of investors' private information is given by the ratio of the total volume of informed transactions (including both buy-informed and sell-informed trades) to over the total trading volume:

$$SDPIN_{i,j} = \frac{\sum V_{i,j}^{B}}{TV_{i,j}}\left(\varepsilon_{i,j} < 0\right) + \frac{\sum V_{i,j}^{S}}{TV_{i,j}}\left(\varepsilon_{i,k} > 0\right) \quad (7)$$

where $V_{i,J}^{B}$ is the volume of buy-informed orders and $V_{i,j}^{S}$ the volume of sell-informed orders; and $TV_{i,j}$ is the total trading volume.

3.3. Measure for earnings management

Total accruals consist of both non-discretionary and discretionary components. In this study, earnings management is proxied by discretionary accruals. We apply different models to estimate this variable and select the performance-adjusted modified Jones (1991) model based on Raman and Shahrur (2008), as it has the highest coefficient of determination (R-squared) at 65.29%. Discretionary accruals or earnings management is calculated as follows:

1. Values of β, β_1, β_2 and β_3 are estimated by Equation (8):

$$\frac{\mathrm{TAC_t}}{\mathrm{TA_{t-1}}} = \beta_0 + \beta_1 \frac{1}{\mathrm{TA_{t-1}}} + \beta_2\left(\frac{\Delta\mathrm{Sales_t} - \Delta\mathrm{Rec_t}}{\mathrm{TA_{t-1}}}\right) + \beta_3 \frac{\mathrm{TFA_t}}{\mathrm{TA_{t-1}}} + \beta_4\mathrm{ROA_t} + \beta_5\,\mathrm{MB_t} + \varepsilon_t \quad (8)$$

2. Non-discretionary accruals are then calculated using Equation (9) with the above-estimated values of coefficients β, β_1, β_2 and β_3:

$$\mathrm{NDAC_t} = \beta_0 + \beta_1 \frac{1}{\mathrm{TA_{t-1}}} + \beta_2\left(\frac{\Delta\mathrm{Sales_t} - \Delta\mathrm{Rec_t}}{\mathrm{TA_{t-1}}}\right) + \beta_3 \frac{\mathrm{TFA_t}}{\mathrm{TA_{t-1}}} + \beta_4\mathrm{ROA_t} + \beta_5\,\mathrm{MB_t} + \varepsilon_t \quad (9)$$

3. Discretionary accruals (operating DAC) can be achieved using Equation (10):

$$\mathrm{DAC} = \frac{\mathrm{TAC_t}}{\mathrm{TA_{t-1}}} - \mathrm{NDAC_t} \quad (10)$$

where DAC is the discretionary accruals (earnings management), $\mathrm{TAC_t}$ is the total accruals (or net operating accruals) estimated by substracting cash flow from operations from net income, TAC_{t-1} is the total assets at the last fiscal year-end; *△Sales* is the change in sales from operations, *△Rec* is the change in accounts receivables, *TFA* is total fixed assets, $NDAC_t$ is non-discretionary accruals, *ROA* is the ratio of total net income to total assets, and *MB* is the ratio of market value to book value of equity.

3.4. Regression models

3.4.1. Single-level Regression Model

In our main model, we regress earnings management (DAC) on informed investors' private information (PI), where DAC is the dependent variable estimated using the modified Jones model (Raman and Shahrur, 2008). The model follows the methodology used by Chen et al. (2007) and Luo (2016). The independent and control variables are estimated for the same time period (quarterly) as the dependent variable. The control variables used are the same as those previous literature - the stock return (RETURN) and institutional investors (INST) – see Chen et al. (2007), La Porta et al. (2000), and Zuo (2016).

$$DAC_{i,t} = \beta_0 + \beta_1 PI_{i,t}^m + \beta_2 RETURN_{i,t} + \beta_3 INST_{i,t} + \beta_4 RETURN_{i,t}\ x\ PI_{i,t}^m + \beta_5 PI_{i,t}^m\ x\ INST_{i,t-1} + \gamma CONTROL_{i,t} + INDUSTRY_{i,t} + YEAR_{i,t} + \varepsilon_t \quad (11)$$

where *i* denotes the stock and *t* denotes the time period. *PI* measures investors' private information, assessed through PIN, DPIN, and the SDPIN for *m* = 1, 2, and 3, respectively; *PI* is a key independent variable in the model, representing the direct impact of confidential information in the stock price on earnings management. *DAC* refers to earnings management (also called discretionary accruals) and is calculated using the modified Jone's (1991) model. *RETURN* represents stock return which is the buy-and-hold return of a firm's stock over the studied quarter. *INST* represents the proportion of firm shares owned by institutional investors. *RETURN x PI* is the interaction term between stock return and investors' private information.[10] We use lagged *PI* to account for firm characteristics that cause returns to contain more private information. *PI x INST* is the interaction term between institutional investors and investors' private information.[11] Other control variables labelled *CONTROL*, include *DUAL* - which indicates *CEO* duality and equals 1 if the *CEO* also serves as the chairman of the board of directors, and 0 otherwise; firm size (*SIZE*) measured by quarterly market capitalization divided by 10^6; firm growth opportunity (*GROWTH*) calculated as the market value of equity plus the book value of assets minus the book value of equity, scaled by the total assets's book value; and profitability (*ROE*).

3.4.2. Multi-level model

[10] Zuo (2016) investigates the relationship between private information and management forecasts, suggesting that the complex nature of confidential information and its acquisition process in stock price makes its relationship with earnings management difficult to observe; the role of its interaction with other dependent variables should not be ruled out. S/he also observed the effect of stock return and its interaction with the variable private information on management forecasts.

[11] We use institutional investors as a factor that can control the quality of the information disclosed by firms especially information presented in the financial reports. Zuo (2016) documents that a higher percentage of shares owned by institutional investors decreases the amount of private information contained in stock prices. We expect that institutional investors can play both direct and mediating roles in our model.

There are various factors underlying managerial decision to manage earnings. We can study earnings management by categorizing the level of factors involved in such decisions, for instance, using firm-level predictors or industry-level predictors (Fan and Jahan-Parvar, 2012; Mackay and Phillips, 2005). It is argued that firms are influenced by factors specific to their industries, which in turn affect their profitability. Notably, the significant variations in profitability among different industries can partly be attributed to differing levels of earnings management across industries. For instance, Beneish (2001) notes that some industries (e.g., financial and insurance industries) have greater incentives for earnings manipulation. This is because factors such as "loan loss reserves for banks and property casualty claim loss reserves" heavily depend on management's discretion (Healy and Wahlen, 1999), leading to a higher likelihood of earnings management due to the flexibility and subjectivity in estimating these reserves.

On the other hand, each industry sector has unique characteristics and information dynamics, making it a valuable resource for speculators looking to uncover new or private insights about specific firms. Additionally, while earnings management is a strategy employed by managers across various industries, there can be notable differences in the extent of earnings manipulation among different sectors. To identify the industry-related patterns in private information and earnings adjustment behaviors, we use a multi-level model to analyze the clustering within our research dataset. This approach allows us to explain variations in private information and earnings management across industry sectors. The application of multi-level modeling in this study contributes to the existing literature.

We identify three levels of earnings management. The first level is observation, the second is the firm level, and the third is the industry level. The multi-level model is gradually expanded from the empty model (Eq. 12) to the model including random intercepts and random coefficients (Eq. 20). Then, we incorporate control variables. The average of private information for each firm (FPI) is a level-two (firm-level) variable. At level-three analysis, the average private information across all firms within each industry (IPI) is used.

3.2.2.1 The empty model

As a first step, we use the empty model to determine whether there is evidence of clustering in the data with respect to the dependent variable DAC_{ijk}.

Level 1: $$DAC_{ijk} = \beta_{0jk} + \varepsilon_{ijk} \quad (12)$$

where DAC represents earnings management (also called discretionary accruals) and is calculated using the modified Jone's (1991) model.

Level 2: $$\beta_{0jk} = \gamma_{00k} + \mu_{0jk} \quad (13)$$

Level 3: $$\gamma_{00k} = \delta_{000} + r_{00k} \quad (14)$$

Combined empty model: $$DAC_{ijk} = \delta_{000} + r_{00k} + \mu_{0jk} + \varepsilon_{ijk} \quad (15)$$

Where DAC is earnings management (also called discretionary accruals) and is computed through the modified Jone's (1991) model.

3.2.2.2 Random models with covariates

The combined model (see below Eq.20) is the combination of Eq.16 to Eq.19 and represents a more integrated mixed-effect model that assumes the intercepts and slopes of certain firm-level variables are random and influenced by firm and industry factors. In other words, this model helps to analyse the indirect effect of sector characteristics on earnings management.

Level 1 equation:

$$\mathrm{DAC_{ijk}} = \beta_{0jk} + \beta_{1jk}\, PI_{ijk}^{m} + \varepsilon_{ijk} \tag{16}$$

where DAC refers to earnings management (also called discretionary accruals) and is calculated using the modified Jone's (1991) model. *PI* measures investors' private information, represented by the PIN, DPIN, and SDPIN for $m = 1, 2,$ and 3, respectively.

Level 2 equation:

$$\beta_{0jk} = \gamma_{00k} + \gamma_{01k}\, \mathrm{FPI_{0jk}} + \mu_{0jk} \tag{17}$$

Where FPI is the average of private information for each firm (level-two, firm-level) variable).

Level 3 equation:

$$\gamma_{00k} = \delta_{000} + \delta_{001}\, \mathrm{IPI_{00k}} + r_{00k} \tag{18}$$

$$\beta_{1jk} = \delta_{110} + \delta_{111}\, \mathrm{IPI_{11k}} + r_{11k} \tag{19}$$

Where IPI is the average of private information across all firms within each industry (level-three, industry-level) variable).

The combined model is given by:

$$DAC_{\mathrm{ijk}} = \delta_{000} + \delta_{001}\, \mathrm{IPI_{00k}} + \gamma_{01k}\, \mathrm{FPI_{0jk}} + \delta_{110} PI_{ijk}^{m} + \delta_{111}\, \mathrm{IPI_{11k}}\ x\ PI_{ijk}^{m} + r_{11k} PI_{ijk}^{m} + \gamma\, \mathrm{CONTROL_{ijk}} + \mathrm{YEAR} + \varepsilon_{ijk} + \mu_{0jk} + r_{00k} \tag{20}$$

where DAC refers to earnings management (also called discretionary accruals), *PI* measures investors' private information, using PIN, DPIN, and SDPIN for $m = 1, 2,$ and 3, respectively. FPI is the average private information of each firm (level-two, firm-level) variable). IPI is the average private information across all firms in each industry (level-three, industry-level variable). Other control variables are labeled CONTROL, including DUAL, which indicates CEO duality and set to 1 if the CEO also serves as chairman of the board of directors and 0 otherwise; firm size (FSIZE) is calculated by quarterly market capitalization divided by 10^6; firm growth opportunity (GROWTH) is measured as market value of equity plus book value of assets minus book value of equity, scaled by the total assets; and profitability (ROE). YEAR is a dummy variable, representing the time effect.

4. Results and discussion

4.1 Main model

Table 2 shows some statistics about our data sample. The average values of investors' private information proxies PIN, DPIN, and SDPIN are 0.158, 0.204, and 0.235, respectively, all with standard deviations around 0.1. These values are relevant because private information is not publicly announced and is only available to a minority of outsiders. Additionally, SDPIN has the highest amount of private information in stock prices, with a mean of 0.235, compared to the other proxies. The R^2 measure indicates how much a stock's price moves together with the market. A higher R^2 means the stock price is more synchronized with the market. The average of R^2 is 0.418, which is higher than the 0.223 and 0.250 reported by Chan and Chan (2014) and Hutton et al. (2009), respectively. This higher R^2 aligns with the notion that stock prices of larger firms reflect more industry and market-specific factors (Roll, 1988) than those of smaller firms. Our sample consists of firms in the S&P 500 index, which is a good proxy for the overall market. However, the average R^2 is below 0.5, indicating that aside from macroeconomic factors, individual stocks have their own unsystematic risk component, and so they move asynchronously with the market.

*****Insert Table 2 around here*****

Earnings management (DAC) is estimated using the performance-adjusted modified Jone's (1991) model by Rahman and Shahrur (2008). The maximum, minimum, and average of earnings management (DAC) are 0.119, -0.127, and -0.005, respectively. DAC can be negative or positive, indicating two forms of earnings management. If positive, it signifies an upward earnings management behaviour; if negative, it indicates downward earnings management. According to Degeorge et al. (1999), earnings management is a managers' game of information disclosure that outsiders must identify. Firms can inflate or deflate their profits following strategies that may change over time. For example, managers may exaggerate earnings to maintain recent performance, that is, to meet at least last year's earnings or to align with shareholders' and investors' expectations, which are connected to the company's reward scheme. Conversely, Holthausen et al. (1995) show that firms' profits are manipulated downward when managers are at the upper limits of their bonuses contracts.

Table 3 presents the correlation matrix of all variables. The correlations of the three pairs formed by PIN, DPIN, and SDPIN have the highest Pearson correlation coefficients, at 0.531, 0.694, and 0.672, respectively. However, these results do not impact the accuracy of the regression models. Instead, they may indicate a close relationship among the three proxies for investors' private information in stock prices. In addition, the pair of firm size (SIZE) and institutional ownership (INST) shows a strong correlation of 0.573. However, the VIF-index check shows normality with no multicollinearity issues. Overall, the correlation coefficients are generally below 0.5, signifying that there are no serious multi-collinearity concerns among the variables.

*****Insert Table 3 around here*****

One issue with the measure of earnings management in Raman and Shahrur's (2008) model is that the proxy can be either negative or positive. The sign of earnings management does not indicate its degree or magnitude but rather its direction. Specifically, a negative value signifies downward earnings manipulation while a positive value indicates upwards earnings manipulation. To address this issue, instead of using the original values of earnings management, we conduct tests for the absolute value of earnings management. Using the absolute value of discretionary accruals when measuring earnings management (Warfield et al., 1995; Hribar and Nichols, 2007) allows for a more accurate assessment of how different factors influence earnings management. In addition to statistical tests, we perform pooled OLS, Fixed Effects, and Random Effects analyses for the main model to determine the best fit for our dataset.

In Table 4, we present the results of the *F* tests and Hausman test. For each model of PIN, DPIN, and SDPIN, the *F* test values are 1028.14, 758.23, and 179.12, respectively, with P values of 0.000; therefore, the Fixed Effects regression is more appropriate than pooled OLS for all models. The Hausman test is then conducted to compare the Fixed Effects and the Random Effects methods. The Chi-square results are 92.06, 15.88, and 104.52 for the PIN, DPIN, and SDPIN models, respectively, with *p*-values 0.000. Consequently, we reject the null hypothesis of the Hausman test, indicating that Fixed Effects is the best fit for our data sample. Additionally, we test for heteroscedasticity and autocorrelation issues. Since, the p-values for both heteroscedasticity and autocorrelation are 0.000 across all models, we reject the null hypotheses of non-heteroscedasticity and non-autocorrelation. To address heteroscedasticity, we run GLS regressions for all models (the results for GLS regressions are shown in Table 3.4 for PIN, DPIN, and SDPIN models).

*****Insert Table 4 around here*****

In Table 4, we also present estimates for how private information contained in share prices affects earnings management. The R^2 values are 0.167, 0.180, and 0.193 for models of PIN, DPIN, and SDPIN, respectively. The SDPIN model demonstrates the best fit with the Fixed Effects regression. PIN shows a significant negative correlation with the absolute values of DAC at the 5% level. Models of DPIN and SDPIN reveal similar patterns, as they negatively influence earnings management, each with a significance level of 1%. The greater amount of confidential information in prices indicates a lower likelihood of earnings management. Therefore, our hypothesis *H1* is confirmed. Through trading, informed investors incorporate their private news into stock prices, causing price movements. Since this type of private information can be known unknown to managers, we argue that it can influence managers' earnings manipulation through either the learning channel or the incentive channel, with the learning channel being less common. When informed traders possess confidential information about firms and incorporate it into stock prices through their trades, managers have fewer opportunities to manipulate earnings, resulting in higher-quaity financial statements issued by firms. This finding encourage external investors to invest more effort in analysing firms and making transactions that can benefit them in many ways.

DAC is positively associated with stock return in the DPIN and SDPIN models. Firm managers with higher stock returns tend to increase the level of accounting profit manipulation, which is consistent with the findings of past studies. For instance, the tests by Zuo (2016) also show positive and significant coefficients on the relationship between stock return and earnings forecasts. This study finds that "the positive coefficient on return is consistent with managers learning from prices, but may not be solely attributed to this channel since it can be partly driven by public information".[12]

The combined effects of stock return (RETURN) and private information (PI) are also shown to be positive and statistically significant at the 1% level (PIN and SDPIN models) and at the 5% level (DPIN model). Firm managers are more responsive to stock returns when stock prices incorporate more new investor information. This finding aligns with our results concering the nature of private information. Incorporating more personal information ito stock prices enhances the connection between stock returns and earnings management by restraining managers from manipulating corporate profits (urging them to reveal the truth) or encouraging managers to acquire new knowledge and integrade it into their decisions.

The coefficients of institutional investors (INST) and the interaction terms between institutional investors and private information of investors in stock prices are both statistically significant at the 1% and 5% levels. This provides evidence that institutional investors constraint earnings distortions. Previous studies indicate that foreign and institutional ownership can effectively monitor and improve a firm's corporate governance (Chung and Zhang, 2011; He et al. 2013). In particular, these outside investors tend to be more interested in stocks from firms with better managerial performance and disclosure (Giannetti and Simonov, 2006). As the most diversified investors, institutional investors usually minimize the risk related to firm-specific information and expect to face only broad-market risk (Farooq and Ahmed, 2014). Our findings support this view and further suggest that, under the moderating influence of institutional investors, the sensitivity of earnings management to private information appears stronger.

Similar to institutional investors, the CEO duality (DUAL) variable acts as a proxy for corporate governance traits that affect earnings management as shown in prior studies (Halioui et al., 2016; Nuanpradit, 2019). DUAL represents the independence of the company's board. Generally, it is

[12] There are studies examining the effect of investor sentiment on earnings management that also agrees that in a period of optimism with a high stock return, companies are used to inflate their accounting profits to respond to high expectations from speculators (see, e.g., Hurwitz, 2018; Santana et al., 2020).

considered poor practice when a firm combines the roles of the CEO and the chairman. Our analysis supports this view, as the results indicate positive and significant coefficients for the impact of CEO duality on earnings manipulation. The likelihood of profit manipulation increases when the same indicidual serves as both the CEO and the chairman executive.

The factor of firm size (SIZE) and profitability (ROE) have statistically significant coefficients at the 1% and 5% levels, respectively, indicating a negative effect on earnings management across all models. Our findings align with those of Dechow and Dichev (2002) and Warfield et al. (1995). Large S&P 500 firms have fewer incentives to manipulate earnings because they are in the public interest and monitored by more analysts and investors. Regarding profitability, well-performing firms can utilize and manage their assets effectively, reducing the need to adjust profits artificially. Firm growth (GROWTH) shows no impact on earnings management, as all coefficients are statistically insignificant.

4.2 Multi-level model

Tables 5 and 6 present the results for covariance parameters and estimates for the Fixed Effects, respectively, using multi-level models. Specifically, Table 5 shows that all estimated parameters across the 3 levels are statistically significant. This suggests we reject the null hypothesis of the Wald *Z* test, implying that the variation in the level 1 outcome and the intercepts at the firm and industry levels are significantly greater than zero. There is clear evidence of non-trivial clustering of observation units within both firm-level and industry-level clusters. The intraclass correlation coefficients (ICC) are also shown in Table 5. ICC (%) serves as an indicator of whether there is evidence of clustered observations within level 2 and 3 units. Overall, all models reveal ICC values for the firm level ranging from approximately 68% to 76%, indicating that over 60% of the variation in earnings management activity occurs between firms. In other words, intrinsic firm characteristics account for the largest proportion of earnings management variation. The observation-unit level accounts for around 20% of the variance in earnings management, while industry-related contribute 5% to 6%. Heck et al. (2014) noted that “5% is often considered a “rough cut-off” of evidence of substantial clustering”. Based on these findings, we conclude that significant clustering exists at both the firm and industry levels. Consequently, multi-level models generally provide a better fit than traditional single-level multiple regression models.

*****Insert Table 5 around here*****

Table 6, presents the estimates for the fixed fffects of the multi-level model. Overall, there is a negative and statistically significant relationship between earnings management and PIN, DPIN, and SDPIN when using multi-level models. The outcomes of the multi-level models still confirm our hypothesis. In addition, the impact of investors’ private information at the firm level (FPI) is also recognized, as their coefficients are negative and significant. However, investors’ private information at the industry level (IPI) shows no significant results across the three models. Our results confirm the essential role of industry-level variables in determining earnings management, but other factors beyond investors' private information at the industry level also play a role (IPI).

*****Insert Table 6 around here*****

4.3 Robustness

4.3.1 Upward and downward earnings management

The concepts of upward and downward earnings management have distinct meanings and implications, each possible influenced by different variables. Combining them in a single regression model can hide some statistical features and relationships. We conduct additional tests to examine how investors' private information affects upward and downward earnings manipulation separately. Table 7 shows the Fixed Effects estimates for PIN, DPIN, and SDPIN models during both upward and downward earnings management. Overall, DPIN and SDPIN impact both downward and upward earnings management as indicated by statistically significant negative coefficients at the 1% level. However, PIN only shows a negative effect on upward earnings management. No significant correlation is found between PIN and downward earnings manipulation. This suggests that DPIN and SDPIN provide a better fit, indicating their advantage over PIN in measuring outsiders' private informationduring higher trading frequencies. In addition, the coefficients for DPIN (-0.739) and SDPIN (-0.212) on upward earnings management are statistically significant at the 5% level; their coefficients for downward earnings management are -0.184 and -0.133, respectively, statistical significance at the 1% and 5% levels. The influence of these three private information measures on stock prices appears stronger in models of upward earnings management than downward. Although investors' private information can affect managers' decisions to inflate or deflate earnings in both cases, managers who have historically inflated earnings may react more strongly to private information.

The factors CEO duality (DUAL) and the interaction between stock return (RETURN) and private information (PIN and SDPIN) influence upward earnings management similarly to the absolute values of earnings management (DAC). However, these control factors show no significant relationship with downward earnings management across all three models involving PIN, DPIN, and SDPIN for the S&P 500. We find that firm growth (GROWTH) is positively related to upward earnings management (using the PIN model) but negatively connected to downward earnings management (using the DPIN model). High market-to-book ratios can limit downward earnings management, whereas the opposite applies to upward earnings management. These contrasting findings about the relationship between market-to-book ratio and earnings management align with the previous literature. For instance, Beatty and Weber (2003) and Sweeney (1994) show evidence of earnings management aimed at avoiding dividend cuts. Growth companies experience strong incentives in the stock market to meet earnings thresholds (Franz, 2014), because the market penalizes these firms more severely when they miss projected earnings targets.

*****Insert Table 7 around here*****

4.3.2 Covid pandemic period

Table 8 shows the results of our second robustness check for the period excluding the COVID-19 era. The 2018-2021 period includes two years of the COVID pandemic, especially 2020 and 2021. During this time, the global economy and stock markets were heavily impacted. The Us stock market has experienced significant declines in the second and third quarters of 2020 and continued to face challenges afterwards. As result, we conduct a robustness check for the non-COVID period covering 2018 to 2019 to verify our findings. Regarding the relationship between earnings management and private information, only the DPIN and SDPIN measures show statistically significant negative coefficients. PIN also exhibits a negative effect on earnings management, but this result is not statistically significant. The results for the variables stock return (RETURN), the interaction term RETURN x PI, and institutional holdings (INST) remain consistent with the main model. However, in the 2018-2019 period, institutional investors (INST) do not play a significant role in the relationship between earnings management and investors' private information in stock prices. Similarly, firm profitability (ROE) appears to have an insignificant impact on the managers' decisions to manage earnings. The market-to-book ratio (GROWTH), however, has positive coefficients that are statistically significant across all three models, indicating that earnings manipulation is more prevalent in firms with higher growth rates.

*****Insert Table 8 around here*****

5. Conclusion

This study contributes to the long-standing and important debate on whether financial markets influence the economy through the managerial learning channel. We examine the impact of investors' private information on managers' decisions regarding earnings management. By using both traditional measures and an alternative measure for private information, we provide the literature with a broader set of measures; we conduct multiple tests to assess the effect of investors' private information on managers' decisions. Our findings indicate that, beyond firm-specific factors, investors' private information is a significant determinant of managers' earnings management decisions, regardless of whether the private information is known or unknown to managers. We offer a new perspective on the managerial learning channel and incentives channel mechanism through which the stock market affects the economy. External investors, although not involved in the day-to-day operations of the firm, can uncover information hidden behind the balance sheets and income statements or generate valuable information that managers are not aware of.

Our methodology differs from previous research by employing a multi-level approach to analyze earnings management. Unlike earlier studies that rely on dummy variables for sector analysis, our method accounts for specific industry factors, including private investor information. This approach allows for a more thorough examination of the relationship, revealing that firm-intrinsic characteristics are the main drivers of changes in earnings management. While industry-level variables are important, we find that they mainly originate from factors beyond investors' private information.

Our findings have significant implications. The reciprocal influence of informed trading improves firms' financial management by reducing discretionary accruals and encouraging transparent corporate disclosures. This assists finance managers in incorporating private information more accurately into their decisions and prompts regulators to ensure proper disclosure of trading order information, which could overall effect overall market efficiency.

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Table 1: This table describes our data sample. PI is the investors' private information which is measured by PIN, DPIN, and SDPIN calculated according to Eq.(3), Eq.(5), and Eq.(7), respectively.

	Companies	**Observations**	**Mean**		
			PIN	DPIN	SDPIN
Industrials	71	1,156	0.136	0.188	0.132
Health Care	63	940	0.228	0.201	0.238
Information Technology	61	952	0.142	0.224	0.267
Communication Services	27	320	0.062	0.144	0.102
Consumer Staples	32	456	0.081	0.775	0.063
Consumer Discretionary	60	880	0.106	0.093	0.089
Utilities	28	384	0.198	0.182	0.134
Financials	61	888	0.137	0.169	0.171
Materials	26	376	0.275	0.156	0.232
Real Estate	25	384	0.176	0.181	0.198
Energy	21	303	0.293	0.201	0.236
Total	475	7,039	0.158	0.204	0.235

Table 2: This table presents the statistical descriptions of regression variables. PIN, DPIN, and SDPIN are the measures for investors' private information, calculated according to Eq. (3), Eq.(5), and Eq. (7), respectively. NSYN is the stock price non-synchronicity measured by Roll (1988)'s market model. DAC is earnings management (also called discretionary accruals) and is computed through the modified Jones model (Raman and Shahrur, 2008); CONTROL variables include: RETURN represents stock return which is the buy-and-hold return of a firm's stock over the period studied (quarterly); INST denotes institutional investors variable, defined by the proportion of firm shares owned by the institutional investors; DUAL is CEO duality and is equal 1 if the CEO of the company also serves as the chairman of the board of directors and equal 0 otherwise; firm size (SIZE) is given by quarterly market capitalization divided by 10^6; GROWTH is firm growth opportunity; ROE presents profitability.

	N	Min	Max	Mean	SD
PIN	7,039	0.002	0.519	0.158	0.124
DPIN	7,039	0.005	0.637	0.204	0.148
SDPIN	7,039	0.006	0.695	0.235	0.121
R-square	7,039	0.213	0.906	0.418	0.357
NSYN	7,039	-0.984	0.568	0.144	0.601
DAC	7,039	-0.127	0.119	-0.005	0.021
RETURN	7,039	-0.819	0.63	-0.131	0.133
SIZE[a]	7,039	6,070	92,914	67,300	0.955
ISNT	7,039	0.461	0.932	0.793	0.174
DUAL	7,039	0.000	1.000	0.493	0.502
GROWTH	7,039	0.081	12.304	2.437	1.312
ROE	7,039	-39.331	37.037	0.265	4.706

[a] Firm size (SIZE) in million US dollars.

Table 3: This table presents the variables correlation matrix. PIN, DPIN, and SDPIN are the measures for investors' private information, calculated according to Eq. (3), Eq. (5), and Eq. (7), respectively. NSYN is the stock price non-synchronicity measured by Roll's (1988) market model. DAC is earnings management (also called discretionary accruals) and is computed through the modified Jones model (Raman and Shahrur, 2008); CONTROL variables include the firm size (SIZE) given by market capitalization divided by 10^6; RETURN represents stock return which is the buy-and-hold return of a firm's stock over the period studied (quarterly); INST denotes institutional investors variable, defined by the proportion of firm shares owned by the institutional investors; DUAL is CEO duality and is equal 1 if the CEO of the company also serves as the chairman of the board of directors and equal 0 otherwise; GROWTH is firm growth opportunity; ROE presents profitability.

	NSYN	DAC	PIN	DPIN	SDPIN	RETURN	INST	DUAL	GROWTH	ROE	FSIZE	VIF
NSYN	1											1.18
DAC	-0.074*	1										3.56
PIN	0.325***	-0.055**	1									2.09
DPIN	0.101**	-0.069**	0.531**	1								1.75
SDPIN	0.363***	-0.032***	0.694**	0.672*	1							4.84
RETURN	-0.218	0.037*	-0.122	-0.105**	-0.033	1						2.66
INST	-0.221**	0.045**	-0.091**	-0.104	-0.037**	0.883	1					1.73
DUAL	0.261**	0.181*	0.134*	0.071**	-0.048	-0.411	-0.383**	1				1.25
GROWTH	0.685	-0.372	0.124	-0.065	-0.019**	-0.218*	-0.221	-0.288	1			1.19
ROE	0.339*	0.744**	0.003	0.04	-0.017	-0.031	-0.014*	0.175***	0.34	1		2.67
SIZE	0.284***	-0.406*	0.019***	-0.274**	-0.238	-0.086	0.573**	-0.194***	-0.072	-0.116**	1	2.36

Note: *, **, and *** indicate p <0.1, 0.05, and 0.01, respectively

Table 4: This table presents results for the relationship between investors' private information and earnings management. PI is the investors' private information, measured by the PIN, DPIN, and SDPIN. DAC is earnings management (also called discretionary accruals) and is computed through the modified Jones model (Raman and Shahrur, 2008); CONTROL variables include the firm size (SIZE) given by market capitalization divided by 10^6; RETURN represents stock return which is the buy-and-hold return of a firm's stock over the period studied (quarterly); INST denotes institutional investors variable, defined by the proportion of firm shares owned by the institutional investors; DUAL is CEO duality and is equal 1 if the CEO of the company also serves as the chairman of the board of directors and equal 0 otherwise; GROWTH is firm growth opportunity; ROE presents profitability. Standard errors are in parentheses.

	PIN Model	**DPIN Model**	**SDPIN Model**
R-Square	0.1669	0.1802	0.1931
F Test	1028.14***	758.23***	179.12***
	Coef. **(SE)**	**Coef.** **(SE)**	**Coef.** **(SE)**
_Cons	0.709	1.023	1.314
PI	-1.148*** (0.361)	-0.557** (0.259)	-1.202*** (0.213)
RETURN	0.838*** (0.034)	0.497*** (0.039)	0.614*** (0.049)
INST	-0.059*** (0.003)	-0.016** (0.008)	-0.040*** (0.006)
RETURN x PI	2.263*** (0.187)	0.557** (0.247)	1.192*** (0.047)
PI x INST	-0.524* (0.318)	-0.269** (0.149)	-0.635** (0.300)
SIZE	-7.2E-07*** (2.1E-07)	-1.3E-07*** (1.1E-08)	-8.5E-07*** (3.6E-08)
DUAL	0.025** (0.012)	0.099** (0.046)	0.099** (0.040)
GROWTH	-0.004 (0.013)	-0.003 (0.013)	-0.008 (0.016)
ROE	-0.162** (0.080)	-0.109** (0.053)	-0.041*** (0.007)
Year Dummies	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes
Hausman Test	92.06***	15.88***	104.52***
Heteroskedasticity	5.83***	11.64***	7.08***
Autocorrelation	1.22E+05***	3.78E+05***	2.28E+06***

Note: *, **, and *** indicate p <0.1, 0.05, and 0.01, respectively

Table 5. This table presents estimates of covariance parameters for multi-level models. PIN, DPIN, and SDPIN are three measures for investors' private information, calculated according to Eq. (3), Eq. (5), and Eq. (7), respectively.

	Null model	**Random- intercept and random-coefficient model**		
		PIN	DPIN	SDPIN
Parameter Estimation				
Individual Obs.	2.072***	1.992***	7.244***	7.085***
Firm Level	5.260***	8.054***	24.637***	25.926***
Industry Level	0.417*	0.588*	2.049*	2.142*
Parameter Estimation (%)				
Individual Obs.	26.74%	18.73%	21.35%	20.15%
Firm Level	67.88%	75.74%	72.61%	73.75%
Industry Level	5.38%	5.53%	6.04%	6.09%

Note: **, **, and *** indicate p <0.1, 0.05, and 0.01, respectively*

Table 6. This table presents the estimates of the Fixed Effects for multi-level models. PI is the investors' private information, measured by the PIN, DPIN, and SDPIN. DAC is earnings management (also called discretionary accruals) and is computed through the modified Jones model; CONTROL variables include the firm size (SIZE) given by market capitalization divided by 10^6; RETURN represents stock return which is the buy-and-hold return of a firm's stock over the period studied (quarterly); INST denotes institutional investors variable, defined by the proportion of firm shares owned by the institutional investors; DUAL is CEO duality and is equal 1 if the CEO of the company also serves as the chairman of the board of directors and equal 0 otherwise; GROWTH is firm growth opportunity; ROE presents profitability. Standard errors are in parentheses.

Parameter	Null model	Random-intercept and random-coefficient model		
		PIN	DPIN	SDPIN
Intercept	-0.011 (0.005)	0.448 (0.106)	0.830 (0.291)	0.110 (0.049)
Year Fixed Effect	No	Yes	Yes	Yes
PI		-2.962** (1.507)	-1.084* (0.633)	-0.969** (0.447)
FPI		-1.125* (0.633)	-1.001** (0.475)	-1.267** (0.642)
IPI		0.540 (0.779)	0.692 (1.284)	-1.100 (1.14)
IPI x PI		-3.306 (3.512)	-1.648 (1.525)	-1.019 (1.137)
RETURN		0.185** (0.100)	0.606* (0.304)	0.953* (0.355)
INST		-0.008** (0.0037)	-0.072** (0.036)	-0.059** (0.029)
SIZE		-8.45E-07*** (3.12E-07)	-5.11-06*** (2.04E-06)	-5.64E-06*** (1.19E-06)
DUAL		0.051** (0.023)	0.138** (0.064)	0.147** (0.073)
GROWTH		0.004* (0.002)	0.009* (0.005)	0.007* (0.003)
ROE		0.276** (0.126)	0.095* (0.054)	0.114* (0.062)

Note: **, **, and *** indicate p <0.1, 0.05, and 0.01, respectively*

Table 7: This table presents results for the relationship between investors' private information and upward and downward earnings management. PI is the investors' private information, measured by the PIN, DPIN, and SDPIN. PIN, DPIN, and SDPIN are the measures for investors' private information, calculated according to Eq.(3), Eq.(5), and Eq.(7), respectively. DAC is earnings management (also called discretionary accruals) and is computed through the modified Jones model (Raman and Shahrur, 2008); CONTROL variables include the firm size (SIZE) given by market capitalization divided by 10^6; RETURN represents stock return which is the buy-and-hold return of a firm's stock over the period studied (quarterly); INST denotes institutional investors variable, defined by the proportion of firm shares owned by the institutional investors; DUAL is CEO duality and is equal 1 if the CEO of the company also serves as the chairman of the board of directors and equal 0 otherwise; GROWTH is firm growth opportunity; ROE presents profitability. Standard errors are in parentheses.

	Upward DAC			**Downward DAC**		
	PIN Model	**DPIN Model**	**SDPIN Model**	**PIN Model**	**DPIN Model**	**SDPIN Model**
R-Square	0.183	0.191	0.194	0.093	0.107	0.133
F Test	701.21***	58.09***	132.53***	209.72***	1,294.2***	507.84***
	Coef. (SE)	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**	**Coef. (SE)**
_Cons	1.522***	1.149***	1.343***	0.537**	0.669*	0.134**
PI	-1.300*** (0.217)	-0.739** (0.344)	-0.212*** (0.005)	-0.681 (0.705)	-0.184* (0.107)	-0.133* (0.074)
RETURN	0.043*** (0.005)	0.026*** (0.001)	0.016*** (0.001)	0.436* (0.240)	0.061 (0.092)	-0.075* (0.044)
INST	-0.003*** (0.001)	-0.008*** (0.003)	-0.011*** (0.003)	-0.021 (0.046)	-0.547* (0.316)	-0.118* (0.065)
RETURN x PI	1.994* (1.010)	3.572* (2.151)	2.049** (1.018)	-1.957 (2.005)	-2.882 (2.194)	1.627 (2.047)
PI x INST	-1.673* (0.996)	-3.380** (1.602)	-1.522** (0.724)	-1.681* (0.974)	-1.445* (0.900)	-0.635* (0.384)
SIZE	-10.1E-06*** (2.7E-07)	-2.3E-05*** (4.4E-06)	-3.4E-06*** (7.2E-07)	-6.8E-05** (3.3E-05)	-4.2E-05** (2.09E-05)	-7.5E-05** (3.9E-05)
DUAL	0.029** (0.015)	0.055** (0.027)	0.108** (0.049)	-0.970 (1.26)	0.688 (0.492)	0.516 (0.737)
GROWTH	0.114 (0.260)	0.023 (0.029)	0.172* (0.095)	-0.018 (0.034)	-0.331* (0.192)	-0.146 (0.220)
ROE	-0.047 (0.037)	0.229 (0.185)	0.104* (0.059)	0.362 (0.384)	-0.175** (0.082)	-0.068* (0.40)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes

*Note: *, **, and *** indicate p <0.1, 0.05, and 0.01, respectively*

Table 8: This table presents results for the relationship between investors' private information and earnings management in the non-covid time from 2018 to 2019. PI is the investors' private information, measured by the PIN, DPIN, and SDPIN. PIN, DPIN, and SDPIN are the measures for investors' private information, calculated according to Eq.(3), Eq.(5), and Eq.(7), respectively. DAC is earnings management (also called discretionary accruals) and is computed through the modified Jones model (Raman and Shahrur, 2008); CONTROL variables include the firm size (SIZE) given by market capitalization divided by 10^6; RETURN represents stock return which is the buy-and-hold return of a firm's stock over the period studied (quarterly); INST denotes institutional investors variable, defined by the proportion of firm shares owned by the institutional investors; DUAL is CEO duality and is equal 1 if the CEO of the company also serves as the chairman of the board of directors and equal 0 otherwise; GROWTH is firm growth opportunity; ROE presents profitability. Standard errors are in parentheses.

	PIN Model	**DPIN Model**	**SDPIN Model**
R-Square	0.104	0.100	0.132
F Test	189.52***	37.40***	76.09***
	Coef. (SE)	Coef. (SE)	Coef. (SE)
_Cons	1.228	0.099	0.563
PI	-2.008 (1.404)	-0.186** (0.088)	-1.210** (0.545)
RETURN	0.075** (0.038)	0.013** (0.061)	0.096*** (0.005)
INST	-0.046** (0.022)	-0.109** (0.051)	-0.038** (0.016)
RETURN x PI	2.953* (1.772)	1.704* (1.022)	0.947** (0.464)
PI x INST	-0.486 (0.630)	0.089 (3.126)	-0.055 (0.081)
SIZE	-8.9E-06*** (6.7E-07)	-1.5E-06*** (4.4E-07)	-2.3E-06*** (2.2E-07)
DUAL	0.020* (0.011)	0.049** (0.025)	0.040* (0.024)
GROWTH	0.009** (0.004)	0.037* (0.061)	0.095** (0.048)
ROE	0.075** (0.033)	0.588* (0.311)	0.161** (0.075)
Year Dummies	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes

***Note:** *, **, and *** indicate p <0.1, 0.05, and 0.01, respectively*