

Post-Earnings Announcement Drift and Ownership Structure in the Modern Japanese Stock Market*

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ABSTRACT

This study investigates the existence of post-earnings announcement drift (PEAD) in the Japanese stock market in the 21st century. Drawing on rational inattention models, which suggest that investors' limited processing capacities cause an underreaction to earnings announcements, this study determines whether the underreaction still exists in the modern Japanese stock market despite the development of technologies that assist investors in processing information. Furthermore, it examines whether the ownership structure, which reflects varying processing costs, affects the results. It reveals three key findings using a sample of 60,124 firm-year observations on the Japanese stock market from 2002 to 2020. First, PEAD decreases over the sample period. Second, it does not decrease in earnings announcements of firms with low foreign investor ownership or high individual investor ownership, indicating that underreaction persists when stocks are traded by investors who do not apply sophisticated technologies and continue to incur higher processing costs. Finally, this study attributes these changes in investors' trading style to an increase in the price response to earnings announcements.

JEL Classifications: G14, M41

Keywords: Post-Earnings Announcement Drift; Rational Inattention; Processing Cost; Ownership Structure; Earnings Announcement

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1. Introduction

Post-earnings announcement drift (PEAD) describes that stock prices gradually incorporate news surprises on the earnings announcement dates over multiple days.¹ Due to its inconsistency with the efficient market hypothesis, which is the premise of portfolio theory, PEAD has been examined for its existence in various countries and considered to be a globally observed phenomenon (e.g., Fink 2021). However, recent studies report that PEAD has disappeared in the United States (US) (Richardson et al. 2010; Chordia et al. 2014; Calluzzo et al. 2019; Martineau 2022). Against this backdrop, this study aims to investigate whether PEAD is still observed in the modern Japanese stock market.

I assume that technological developments assist investors in processing earnings announcement information and explore whether a decrease in the information processing cost can lead to a reduction in PEAD. Specifically, I examine whether there is a decline in PEAD over time and whether the ownership structure influences the trend. Rational inattention models assume that investors' limited processing capacity results in underreaction to earnings announcements (Blankespoor et al. 2020), and the 21st century has witnessed innovations in technology that lower the information processing cost. For example, large asset management firms—expecting to leverage the latest technologies to enhance their investment performance-have established research and development (R&D) departments. Additionally, the Tokyo Stock Exchange (TSE) introduced technological innovations, such as eXtensible Business Reporting Language (XBRL) in 2008 and Arrowhead in 2010, which facilitate quick access to financial data and trade of stocks. The prevalence of these technological advances in the 21st century is expected to lead to a decrease in PEAD over time. However, the benefits of technological development may not be equally distributed among investors. It is reasonable to assume that large, more sophisticated investors are better positioned to benefit from technologies. Thus, PEAD may not decline for firms owned by small, less sophisticated investors.

This study evaluates whether the reduction of information processing costs due to technological development has led to a decrease in PEAD, using a sample of the Japanese market in the 21st century. Two reasons drive the focus on the 21st century. First, there have been two significant technological events in the TSE—the introduction of XBRL and Arrowhead, which affect the information processing cost as shown in prior literature. Second, the 21st century is marked by the third Artificial Intelligence (AI) boom, which is characterized by machine learning and deep learning (Matsuo 2015). Technological development is non-linear; it occurs in breakthroughs, followed by stagnation. Following the first and second AI booms, the 21st century can be considered the era of the third AI boom.² For example, in the early 2000s, the development of the Web made large amounts of data available, and research on machine learning techniques advanced. In 2012, the "Super Vision," developed by a team at the University of Toronto, led to the spread of deep learning technology. The technologies of the third AI boom may have been introduced into investors' trading strategies, lowering the cost of information processing. This study focuses on the Japanese market because some stocks are less likely to be traded by investors who use sophisticated technologies. Foreign and individual investors conduct more than 90 percent

¹ This study focuses on not only earnings surprise information but also the entire information disclosed in the earnings announcements (Section 4).

² The first AI boom was in the late 1950s-1960s, and the second AI boom was in the 1980s.

3

of trading in Japan. While most foreign investors are considered sophisticated institutional investors and have access to cutting-edge technology, individual investors are less likely to use sophisticated technology (Cready 1988; Bhattacharya 2001). Previous research shows that foreign investors prefer well-known firms, such as stocks with a high percentage of overseas sales, and those included in the Morgan Stanley Capital International (MSCI) index (Miyajima and Ogawa 2016). Using Japan as a sample, we can explore whether there is a difference in the trend of PEAD between stocks traded by foreign investors who use sophisticated technology and those who do not. According to Iwatsubo and Watikins (2021, 2), "The TSE is the only developed market exchange that provides long-term and consistent data on stock transactions classified by investor type". In other countries such as the US, it is difficult to design appropriate research studies owing to the lack of publicly available data.

This study analyzes a sample of 60,124 firm-year observations listed on the Japanese equity market from April 2002 to March 2020, measuring the underreaction to earnings announcements at the year level using an unbiased regression model (Biais et al. 1999). Consistent with the prediction, PEAD decreases during the sample period. Further analysis reveals that this trend depends on the ownership structure, with PEAD decreasing only in the earnings announcements for firms-year with high levels of foreign ownership or low levels of individual ownership. This finding aligns with the prediction that sophisticated investors are more likely to use the latest technologies, and technological improvements contribute toward the mitigation of PEAD. To complement the primary analysis, this study conducts two additional analyses. First, to explore whether the observed decrease in PEAD results from enhanced price sensitivity to earnings announcements, this study uses abnormal return variance (AVAR) as a proxy for price response to earnings announcements. The results show that AVAR increases more in earnings announcements of firms with high foreign investor ownership or low individual investor ownership, indicating that the newest technologies enable investors to process information more quickly, thereby mitigating PEAD. Next, to investigate the potential impact of regulation fair disclosure on PEAD, this study analyzes the enactment of the regulation in Japan in 2016. The regulation was implemented to prevent the leakage of private information before earnings announcements. Following a priceleads-earnings analysis, the study demonstrates that the ability of stock price to predict earnings surprises weakened and reactions to earnings surprises increased after the regulation. However, the results do not indicate that the observed decrease in PEAD is influenced by the regulation of fair disclosure.

This study contributes to the literature in three ways. First, the findings of this study confirm that PEAD has decreased in the Japanese stock market, consistent with prior evidence in the US. Although PEAD is considered a global phenomenon (Ball and Brown 2019; Fink 2021), its disappearance has only been evident in the US market (Richardson et al. 2010; Chordia et al. 2014; Calluzzo et al. 2019; Martineau 2022). Using non-US data, this study further supports the possibility that PEAD has declined in the 21st-century stock market rather than resulting from fortuity in the US market. The study's findings differ from previous Japanese literature on PEAD (Okada and Saeki 2014; Jin 2019) in two ways. First, this study focuses on the time-series trend of PEAD. Although Jin (2019) examines the trend of PEAD around the introduction of XBRL, to the author's knowledge, this study is the first to examine the long-term trend of PEAD in the 21st century. Second, it focuses on the underreaction to the entire information of the earnings announcement rather than just the earnings surprise, which other Japanese literature has examined. This approach enables the study to examine the influence of technological development on the

ability to process more complex information, making a unique contribution to the Japanese literature on PEAD.

Second, it contributes to the emerging accounting field of research on the rational inattention model (Blankespoor et al. 2020). Using the Japanese market environment, in which more than 90 percent of the changes in trading volume (in JPY) are caused by foreign and individual investors, this study finds that PEAD remains in firms with low foreign ownership and high individual ownership. This suggests that the limitation of processing capacity affects underreaction, supporting the implications of rational inattention models. These findings are important for firms, because a change in investors' processing costs may alter the optimal level of disclosure.

Finally, this study contributes to the literature on the cause of the increase in price responses to earnings announcements. Beaver et al. (2018) assert that the price response to earnings announcements is dramatically increasing and that this trend is quite different from the past; many studies have sought to explain this reason. While some studies suggest that the increase may be attributed to accounting information other than earnings (Hand et al. 2022; Barth et al. 2023), others report that changes in investor trading styles may impact the price reactions to earnings announcements (Lee and Watts 2021; Thomas et al. 2022). The findings of this study highlight the importance of changes in investor trading styles as a contributing factor.

The remainder of this study is organized as follows. Section 2 introduces the Japanese shareholder trend. Section 3 reviews the literature and develops hypotheses. Section 4 describes the methodology and samples. Section 5 presents the results. Section 6 conducts the robustness analysis, followed by additional analyses in Section 7. Finally, Section 8 concludes the study.

2. Trend of Shareholder Composition in Japan

The ownership structure of Japanese publicly traded companies has drastically changed over the past five decades. Figure 1 depicts the shareholder distribution and stock market status in Japan. Banks and business firms were the predominant shareholders in Japan until the late 1990s. However, owing to the banking crisis in 1997 and changes in the accounting system, such as the market evaluation of cross-shareholdings in 2002, these bank stock holdings and crossshareholdings fluctuated in the late 1990s. Consequently, foreign investors replaced banks and business firms as the main shareholders of Japanese stocks.

Panel A of Figure 1 illustrates the trend in the Japanese shareholding ratio by shareholder type. In 1991, financial institutes and business corporations accounted for 43% and 29%, respectively, whereas in 2019, they constituted 30% and 22%, respectively. Conversely, foreign investors' proportion increased from 6% in 1991 to 30% in 2019.

Panel B displays the trend in trading volume (in JPY) by shareholder type. Similar to the shareholding ratio, the financial institutes' trading volume (in JPY) decreased after the bank crisis. In contrast, foreign investors' trading volume (in JPY) has increased since 2000 and reached 71% in 2019, indicating that they are the most popular traders in the current Japanese stock market. Additionally, individual investors represented the second-highest shareholder type in 2019, with 91% of the total trading volume (in JPY) coming from foreign and individual investors. Therefore, foreign and individual investors are the primary drivers of information into the Japanese stock market prices.

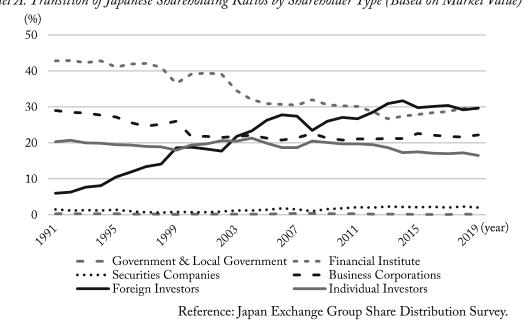
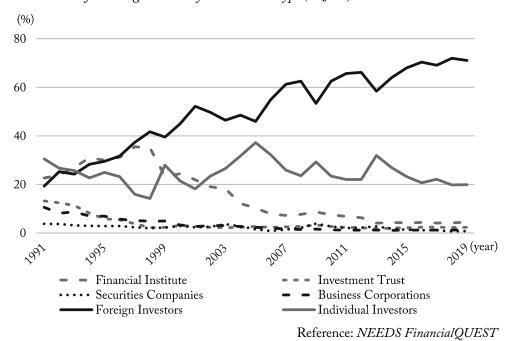


FIGURE 1. TRANSITION OF JAPANESE SHAREHOLDING RATIOS AND TRADING VOLUMES Panel A: Transition of Japanese Shareholding Ratios by Shareholder Type (Based on Market Value)

Panel B: Transition of Trading Volumes by Shareholder Type (in JPY)



3. Related Literature and Hypotheses

3.1. Prior Literature

3.1.1. Disappearance of PEAD

PEAD is the underreaction to news surprise or the phenomenon in which stock prices gradually incorporate the initial surprise over multiple days. Ball and Brown (1968) first mentioned PEAD in their seminal research and, Bernard and Thomas (1989) provided more convincing evidence. After that, numerous empirical studies have been conducted as evidence of efficient hypothesis anomalies (Fink 2021).

Recent research indicates that PEAD is disappearing from the US stock market (Richardson et al. 2010; Chordia et al. 2014; Calluzzo et al. 2019; Martineau 2022), which is attributed to liquidity improvement (Chordia et al. 2014), active trading of low latency traders (Chordia and Miao. 2020), and dissemination of its existence since its publication (Calluzzo et al. 2019). However, because the contribution of each factor towards PEAD is still uncertain, it remains unclear whether this discovery is observed only in the US or in other countries with different features.

3.1.2. Ownership Structure and PEAD

Previous studies have demonstrated a correlation between investor type and PEAD, with naive investors who lack an understanding of the time-series characteristics of earnings being identified as the cause of PEAD (Bernard and Thomas 1989). It is generally believed that institutional investors are sophisticated, whereas individual investors are unsophisticated and naive (Bernard and Thomas 1989). Consistent with this assumption, prior studies have established that higher institutional ownership reduces PEAD (Bartov et al. 2000; Shu 2013), and transient institutional investors also decrease PEAD (Ke and Ramalingegowda 2005). Moreover, foreign institutional investors reduce mispricing (Qin and Bai 2014; Shin and Park 2018) and accelerate the speed of price discovery (Cai et al. 2020). While Hirshleifer et al. (2008) and Kaniel et al. (2012) contend that the trading behaviour of individual investors is not necessarily naive, Bhattacharya (2001) and Battalio and Mendenhall (2005) argue that small and less sophisticated individual investors are the naive investors are institutional investors including pension funds, investment trusts, insurance companies, and hedge funds based abroad. Given the high volume of transactions (Section 2), most investors are assumed to be sophisticated and transient institutional investors.

3.2. Hypotheses Development

One explanation for PEAD's existence is that its costs outweigh its benefits. These costs include direct costs (e.g., transaction costs) (Bhushan 1994; Ng et al. 2008) and indirect costs such as information processing costs (Blankespoor et al. 2020; Fink 2021). Blankespoor et al. (2020) identify three processing costs: awareness, acquisition, and integration, each derived from information processing steps that acknowledge the existence of disclosure, extract value-relevant information from the disclosure, and analyze information related to firm value.

³ In addition to research that focuses on institutional investors (foreign investors) and individual investors, some studies have investigated the effect of high-frequency traders (Bhattacharya et al. 2020; Ke and Zhang 2020; Chakrabartya et al. 2022) and low latency traders (Chordia and Miao 2020).

Rational inattention models assume that investors have limited processing capacity and allocate scarce resources to process information rationally (Veldkamp 2011). Empirical evidence suggests that these processing costs are related to PEAD. For example, Hirshleifer et al. (2009) and Blankespoor et al. (2020) find that PEAD is stronger when many firms announce earnings on the same day. Moreover, Barinov et al. (2022) suggest that PEAD is stronger for conglomerates than for single-segment companies, and Kang et al. (2017) report that it increases with the degree of international diversification.

However, technological advancements in the 21st century are expected to decrease these information processing costs. For example, large investment management firms have established their own R&D departments to research and develop operational methods using cutting-edge technology. The website of Mitsubishi UFJ Trust Investment Technology Institute, a subsidiary and research division of a major Japanese investment management firm, states that it is enhancing and automating business efficiency using robotic process automation and analyzing information using data analysis techniques such as AI and machine learning.⁴ Bhattacharya et al. (2018) provide evidence that larger institutional investors have already adopted comparable technologies before the introduction of XBRL. Therefore, investors are expected to regularly engage in R&D activities that incorporate state-of-the-art technology to enhance their operational performance and reduce investors' awareness, acquisition, and integration costs.

Another example of technological innovations is the introduction of XBRL and Arrowhead. XBRL, a standardized XML-based language, was introduced in 2008 to promote the creation, distribution, and use of financial information. It facilitates direct data import into systems and spreadsheets, thus enabling investors to process and analyze data without re-entering them. The introduction of XBRL is anticipated to reduce acquisition and integration costs (Blankespoor 2019). Similarly, Arrowhead and co-location services were introduced by TSE on January 4, 2010, reducing order processing time from 3 seconds to 5 milliseconds. Since then, Arrowhead has been renewed three times, with order response times decreasing to less than 1 millisecond in July 2012, 0.5 milliseconds in September 2015, and 0.2 milliseconds in November 2019. This innovation has accelerated the entry of high-frequency trading (HFT) firms into the Japanese market, and it is believed that approximately 40 percent of trading volume (in JPY) is executed via co-location services to achieve HFT (Ohyama et al. 2021). HFT is a type of algorithmic trading in which orders are automatically determined and placed by a computer in accordance with a predetermined program without human intervention. Chakrabartya et al. (2022) demonstrate that HFT mitigated human cognitive limitations and increased market reaction to US firms' earnings announcements. Thus, the increased use of algorithmic trading, including HFT, is expected to significantly reduce the integration costs associated with investors analyzing information.

Based on the technological advancements of both investors and the exchange market, it is anticipated that the information processing cost in the 21st-century Japanese stock market has decreased. Therefore, if the primary cause of PEAD is information processing costs, PEAD is expected to decline over time. Accordingly, the following hypothesis is proposed:

Hypothesis 1: PEAD is decreasing in the Japanese stock market.

⁴ Available at: https://www.mtec-institute.co.jp/en/business/data_analytics/.

The impact of technological advancements on investors' information processing costs is expected to vary based on the investors' size and sophistication (Blankespoor et al. 2020). Larger investors tend to benefit more from economies of scale and can afford cutting-edge, expensive equipment and skilled labor. Moreover, the reduction of marginal information processing costs resulting from the implementation of the technology is greater for sophisticated investors.

In the early stages of XBRL adoption in the US, information asymmetries between individual and institutional investors increased (Blankespoor et al. 2014), suggesting that institutional investors were better equipped to benefit from XBRL. As individual investors are smaller and less sophisticated than institutional investors, the cost of mastering XBRL could outweigh its benefits. Therefore, individual investors may rationally choose not to use XBRL, and its introduction would not reduce the cost of information acquisition or integration for them, explaining the existence of PEAD. The effects of HFT and algorithmic trading, and R&D capabilities may vary between individual and foreign investors. According to Ohlson's (1975) theory, the value of information increases with the size of the investor's wealth, and research indicates that individual investors tend to use less costly information (Cready 1988; Bhattacharya 2001). HFT and algorithmic trading, and R&D activities require expensive equipment or advanced skills, making these technologies more accessible to larger and more sophisticated institutional investors. Thus, individual investors with less wealth may continue to incur higher integration costs, while foreign investors can reduce information acquisition and integration costs by utilizing cutting-edge technology, thereby reducing PEAD.

Individual and foreign investors constituted approximately 90 percent of the trading volume (in JPY) in the Japanese stock market in 2019 (Section 2). If individual and foreign investors conduct 90 percent of all trades on the day of the earnings announcement, the impact of technological developments on PEAD may differ between stocks primarily traded by foreign investors and those by individual investors. Hence, the following hypotheses are derived.

Hypothesis 2.1: PEAD persists in firms with low levels of foreign ownership. Hypothesis 2.2: PEAD persists in firms with high levels of individual ownership.

Hypotheses 2.1 and 2.2 assume that sophisticated and unsophisticated investors set the stock price (Hand 1990), the proportion of shareholdings is correlated with a percentage of actual trades, and the investor group with a high proportion of shareholdings sets the stock price. However, a high foreign (individual) ownership ratio does not necessarily indicate that foreign (individual) investors set the stock price on the earnings announcement date, as the ownership structure merely reflects who owns the shares.

To address this issue, cut-off points are employed as a narrow solution, following Balsam et al. (2002) and Collins et al. (2003). Specifically, I examine whether PEAD decreases in the sample with a low level of foreign ownership (a high level of individual ownership), by not treating foreign (individual) ownership as a continuous variable. This is because, in a sample with a low level of foreign ownership (high level of individual ownership), foreign investors (other investors besides individual investors) are unlikely to determine the stock price on the day of the earnings announcement. Overall, the hypotheses are tested by verifying whether PEAD decreases in samples where the necessary conditions are unmet.

9

4. Methodology and Data

4.1. Research Design

Two methods are used to detect PEAD: one focuses on earnings surprises and subsequent returns, while the other focuses on returns on the day of the earnings announcement and subsequent returns. The first method, applied by seminal studies such as Ball and Brown (1968) and Bernard and Thomas (1989), uses the difference between actual earnings and market expectations as the earnings surprise, which is a standard research design for studying PEAD. However, calculating the earnings surprise requires unobservable expected earnings, which may produce unintended results due to estimation errors. Furthermore, earnings announcements contain information other than earnings (e.g., other financial information such as sales and R&D expenditure and non-financial information such as management forecasts and management conference calls) that earnings surprises do not capture. To address these issues, the latter approach, using an unbiased regression model introduced by Biais et al. (1999), is effective. This model assumes that future prices will be "efficient" prices and regresses the price change in the future (typically sixty business days) on the price change around the announcement date. The results of this regression help determine whether there is any information that the stock price does not incorporate on the earnings announcement date.

This study detects PEAD using an unbiased regression approach because the interest is the improvement of processing costs for fundamental information including non-earnings information, which has become increasingly significant in recent years. For example, Nallareddy et al. (2020) show that cash flows have more explanatory power for future cash flows than earnings. Hand et al. (2022) demonstrate that eleven income statement-related item surprises and two cash flow statement-related item surprises significantly correlate with the stock price. Barth et al. (2023) classify firms into four groups (new economy or non-new economy, profit or loss) to demonstrate that the accounting items strongly associated with stock prices vary by group.^{5,6} Given that this study examines whether technological advancements have reduced the information processing cost of acquiring and integrating the entire information disclosed in the earnings announcement, a return approach that emphasizes the entire information disclosed in earnings announcements is adopted. In addition, stock prices respond not only to earnings surprises (the difference between actual earnings and the market's expected earnings for the current period) but also to management forecast surprises (the difference between management earnings guidance and market's expected earnings for the following period). As nearly all Japanese companies release earnings forecasts for the following fiscal year on the day of earnings announcements, it is unclear which of the two factors, realized earnings surprises or management forecast surprises, should be used to identify PEAD. Accordingly, this study measures PEAD by returns. However, a similar analysis is also conducted using earnings surprises in Section 6.

Following prior research (Biais et al.1999; Martineau 2022), the following model is estimated annually to detect PEAD:

⁵ Barth et al. (2023) identify key items in each group: net income and book value of net assets (for non-new economy and profit firms), book value of net assets (for non-new economy and loss firms), net income and operating cash flow (for new economy and profit firms), and cash, book value of net assets, total assets, and R&D expenditures (for new economy and loss firms).

⁶ Moreover, Shao et al. (2021) reveal that the relationship between earnings and stock prices has weakened, however the relationship between fundamental news and stock prices, as measured by earnings announcement returns, has increased.

$$\mathcal{A}R_{i,y}^{-1,\,60} = \beta_0 + \beta_1 \mathcal{A}R_{i,y}^{-1,\,1} + \varepsilon_i \tag{1}$$

The dependent variable $(AR_{i,y}^{-1, 60})$ is the post-earnings announcement return for firm *i* in fiscal year *y*, which is defined as the buy-and-hold abnormal return from earnings announcements -1 to +60 business days. The explanatory variable $(AR_{i,y}^{-1, 1})$ is the abnormal return around the earnings announcement of firm *i* in fiscal year *y*, which is defined as the cumulative abnormal announcement window return over three days (earnings announcement date ± 1). I estimate abnormal returns in two ways using the market model and the Carhart four-factor model (Carhart 1997). I estimate α_i and γ_i for each firm-year over the non-earnings-announcement windows (from day -260 to day -3 relative to the date of the annual earnings announcement date) from the following equations: Market model:

$$Return_{i,d} = \alpha_i + \gamma_i M P_d + \varepsilon_{i,d}$$
(2),

Carhart four-factor model:

$$Return_{i,d} = \alpha_i + \gamma_{1,i} MP_d + \gamma_{2,i} SMB_d + \gamma_{3,i} HML_d + \gamma_{4,i} MOM_d + \varepsilon_{i,d}$$
(3),

where *Return*_{*i,d*} is the daily stock price return of firm *i* at day *d*, *MP*_{*d*}, *SMB*_{*d*}, *HML*_{*d*}, and *MOM*_{*d*} are the corresponding market returns, size returns, book value returns, and momentum returns at day *d*, respectively. The daily factor returns data (*MP*_{*d*}, *SMB*_{*d*}, *HML*_{*d*}, and *MOM*_{*d*}) are obtained from Kenneth R. French Data Library.⁷ To adjust for the effect of the exchange rate (Glück et al. 2021), I convert the downloaded factors into Japanese JPY. Refer to Appendix A for further details of the adjustment method. When the content of the earnings announcement is not fully reflected in the stock price on the earnings announcement date, the drift continues and β_1 should be higher (Biais et al. 1999; Ball and Shivakumar 2008).

4.2. Data

All data are acquired from the *NEEDS-FinancialQUEST* database of Nikkei, Inc. The sample consists of 60,124 firm-year earnings announcements excluding financial sector entities (e.g., banks, securities, and insurance) listed in the Japanese equity market from April 2002 to March 2020.^{8,9,10} Observations with a difference greater than sixty days between the fiscal year-end date and announcement date are removed. Additionally, when estimating beta from the market model or Carhart four-factor model, the observations with fewer than forty returns are excluded. The sample

⁷ Daily MP, SMB, and HML returns are obtained from "Fama/French Japanese 3 Factors [Daily]" and daily MOM returns are obtained from "Japanese Momentum Factor (Mom) [Daily]" in Kenneth R. French Data Library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

⁸ Considering the possibility that the earnings announcement is released after the stock market closes, I defined earnings announcement day as the business day after the earnings announcement day in the database.

⁹ The accounting period of most Japanese firms ends in March. In this study, I classify announcements that end from April 2002 to March 2003 as fiscal year 2003, and April 2003 to March 2004 as fiscal year 2004, and so on.

¹⁰ When the announcement day is different between the consolidated and non-consolidated financial reports, I choose the latter because it is released faster. However, as over 95 percent of firms release them on the same day, this choice has negligible effect on the results.

is restricted to those that utilize all variables in this analysis. Finally, I winsorize all continuous variables at 0.5% and 99.5% of their respective distribution to reduce the effects of outliers.

The shareholder composition data utilized for this analysis is the number that is described in the security report. Annually, Japanese corporations report six categories of shareholder distribution in the security report: "government and local governments," "financial institutes," "financial institutes," "financial instruments businesses," "other business firms," "foreign investors," and "individual investors." The ratios of foreign and individual ownership used in this study are obtained from the NEEDS-FinancialQUEST database.

Panel A of Table 1 displays the descriptive statistics for the foreign ownership (*FOR*) and individual ownership (*IND*) ratios by fiscal year. The number of observations remained relatively stable, with the highest number being 3,557 in the fiscal year ending between April 2006 and March 2007 (fiscal year 2007) and the lowest being 3,127 in the fiscal year ending between April 2012 and March 2013 (fiscal year 2013). Foreign investor ownership has been increasing over time (Section2). In the fiscal year ending between April 2002 and March 2003 (fiscal year 2003), the mean (median) rate is 5.0% (1.1%), while in the fiscal year ending between April 2019 and March 2020 (fiscal year 2020), it rises to 12% (7.3%). Conversely, the ownership of individual investors remained relatively stable, with maximum mean (median) of 47 % (45 %) and a minimum mean (median) of 43% (41%).

To test Hypotheses 2.1 and 2.2, I establish the thresholds for high and low foreign ownership and individual ownership. Although there is no theoretical justification, I use each fiscal year's twentieth and eightieth percentile as the cut-off points, consistent with previous research (Hand et al. 2022; Martineau 2022). Panel A of Table 1 presents the twentieth percentile of the foreign ownership ratio and the eightieth percentile of the individual ownership ratio. The maximum of the twentieth percentile of the foreign ownership ratio is 1.3%, and the minimum is 0.1%. The maximum of the eightieth percentile of the individual ownership ratio is 68%, and the minimum is 62%.

Panel B of Table 1 shows the overlap of the subsamples using a 2×2 matrix table with rows of *FOR* and columns of *IND*. If observations with less than (more than) the twentieth percentile for foreign investors are classified into groups with more than (less than) the eightieth percentile for individual investors, the two groups may represent two sides of the same coin. The results in Panel B indicate this possibility. If foreign and individual investors' distribution are independent, the number of observations in less (more) than the twentieth percentile and more (less) than the eightieth percentile should be 2,405 (38,479). However, the actual number of observations is 3,868 (39,942), which indicates that firms classified into Low *FOR* (High *FOR*) are more likely to be classified into High *IND* (Low *IND*). Consequently, this study's results using foreign or individual investors as cut-off points are not necessarily completely different but are the results of using a sample of observations with relatively low (high) foreign ownership and relatively high (low) individual ownership from two distinct perspectives. TABLE 1. DESCRIPTIVE STATISTICS OF SHAREHOLDER OWNERSHIP

FY	N		FOR			IND	
		Mean	Median	P20	Mean	Median	P80
2003	3,291	0.050	0.011	0.001	0.436	0.418	0.626
2004	3,282	0.064	0.021	0.001	0.440	0.422	0.637
2005	3,379	0.076	0.035	0.004	0.437	0.416	0.636
2006	3,432	0.093	0.051	0.006	0.427	0.405	0.624
2007	3,557	0.094	0.049	0.005	0.439	0.416	0.647
2008	3,501	0.091	0.044	0.004	0.449	0.426	0.665
2009	3,342	0.075	0.030	0.002	0.461	0.439	0.669
2010	3,367	0.077	0.029	0.001	0.467	0.446	0.679
2011	3,287	0.079	0.030	0.002	0.467	0.446	0.677
2012	3,237	0.080	0.028	0.001	0.464	0.441	0.673
2013	3,127	0.084	0.031	0.002	0.461	0.438	0.663
2014	3,197	0.097	0.042	0.004	0.449	0.428	0.651
2015	3,249	0.105	0.051	0.005	0.442	0.423	0.648
2016	3,272	0.107	0.055	0.007	0.443	0.422	0.649
2017	3,358	0.110	0.060	0.008	0.443	0.421	0.657
2018	3,384	0.116	0.068	0.012	0.433	0.407	0.642
2019	3,419	0.115	0.070	0.012	0.433	0.408	0.640
2020	3,443	0.115	0.073	0.013	0.437	0.415	0.636
Total	60,124	0.091	0.041	0.013	0.446	0.423	0.624

Panel A: Descriptive Statistics

Panel B: Sample Distribution

	Low IND	High <i>IND</i>	Total
Low FOR	8,166 (9,629)	3,868 (2,405)	12,034
High FOR	39,942 (38,479)	8,148 (9,611)	48,090
Total	48,108	12,016	60,124
	Pears	x = 1,400	Pr = 0.000

Notes: Panel A displays the descriptive statistics of *FOR* and *INV* by fiscal year. Panel B represents the sample joint distribution using a 2×2 matrix table with rows of *FOR* and columns of *IND*. The values in parentheses are the number of samples when *FOR* and *IND* were independent. Please see the definitions of *FOR* and *IND* in the Appendix B.

5. Results

5.1. Visual Results

Figure 2 displays the average cumulative abnormal returns following earnings announcements. I divide the observations for each fiscal year into ten groups based on the magnitude of the abnormal return on the day of the earnings announcement. I then calculate the mean cumulative abnormal return values for each group over the period of +2 to +60 business days after the earnings announcements. To visualize this trend, I divide the sample period into four-time intervals: FY 2003–FY 2007, FY 2008–FY 2011, FY 2012–FY 2015, and FY 2016–FY 2020. Figure 2 illustrates these results, only for group 2 (with the second-lowest abnormal returns on earnings announcements) and group 9 (with the second-highest abnormal returns on earnings announcements), to facilitate reading.¹¹

Figure 2 shows that group 9 exhibits higher cumulative abnormal returns following earnings announcements compared with group 2, indicating that investors are unable to fully incorporate positive or negative news on the earnings announcement day and such news is gradually reflected in stock prices. Comparing the results from the four periods reveals that the difference in cumulative abnormal returns between groups 2 and 9 decreases from period 1 to period 4, suggesting a decline in PEAD over the sample period.

5.2. Regression Results

Figure 3 displays the regression results of PEAD. Each fiscal year, equation (1) is regressed, and coefficient β_1 is obtained. Panel A of Figure 3 presents the estimated β_1 for the full sample. When the stock price underreacts (overreacts) to earnings announcements, β_1 should be higher (lower). In the early sample period, stock prices tend to underreact to earnings announcements. However, the situation has improved in recent years, indicating a decrease in PEAD in the sample period.

Panels B and C report the results of the subsample analysis. Equation (1) is separately regressed each fiscal year for firms with high foreign ownership (individual ownership) and low foreign ownership (individual ownership) at the twentieth percentage point (eightieth percentage point) cut-off. Panel B presents the results for foreign investors. In the sample above the twentieth percentage point (High FOR), β_1 decreases, as in Panel A. However, in the below twentieth percentage point sample (Low FOR), β_1 does not decrease, suggesting that PEAD persists in firms with low foreign shareholder ownership. Panel C presents the results for individual investors. In the below eightieth percentage point sample (Low *IND*), β_1 does not decrease, as in Panel A. Nevertheless, in the above eightieth percentage point sample (High *IND*), β_1 does not decrease, revealing that PEAD persists in firms with high individual shareholder ownership.

Table 2 presents the results of the OLS regression of β_1 on the trend variable *T*, which takes the value 1 if the fiscal year is 2003, 2 if 2004, and so on. Panel A shows the results of the market model, while Panel B shows the results of the Carhart four-factor model. Column (1) represents the full sample (Panel A of Figure 3), columns (2) and (3) represent the foreign investor subsample (Panel B of Figure 3), and columns (4) and (5) represent the individual investor subsample (Panel C of Figure 3). Similar to Figure 3, the coefficients *T* are negative and statistically significant in the full sample (column 1), High *FOR* (column 2), and Low *IND* (column 4). Conversely, the *T* coefficients are not statistically significant in Low *FOR* (column 3) and High *IND* (column 5).

¹¹ Groups 2 and 9 were chosen instead of groups 1 and 10 to mitigate the effect of outliers.

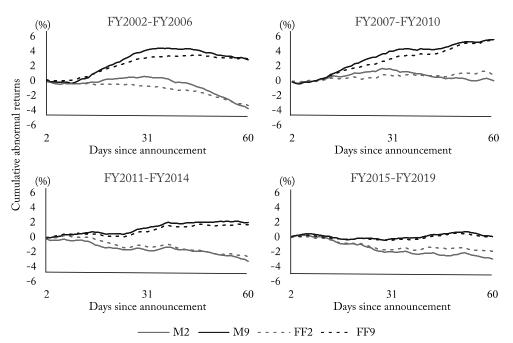


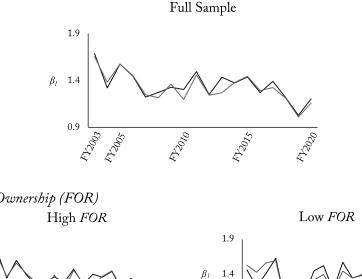
FIGURE 2. AVERAGE CUMULATIVE ABNORMAL RETURNS AFTER EARNINGS ANNOUNCEMENT

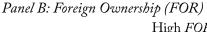
Notes: The figure depicts the average cumulative abnormal returns following earnings announcements by each group. For clarity, only the results for group 2 (the second-lowest abnormal returns on earnings announcements) and group 9 (the second-highest abnormal returns) are presented, although observations are divided into 10 groups. "M2 (M9)" is the result for group 2 (group 9) calculated by the market model, and "FF2 (FF9)" is the result for group 2 (group 9) calculated by the Carhart four-factor model.

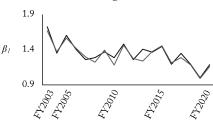
In conclusion, Figure 3 and Table 2 indicate that PEAD decreases from the fiscal year ending between April 2002 and March 2020. However, this trend is not observed in the earnings announcements of firms with low levels of foreign investor ownership or high levels of individual investor ownership. These findings support the hypothesis that foreign investors can benefit more from the evolution of technologies than individual investors, resulting in relatively low processing costs and rapid incorporation of information into stock prices. When the foreign shareholder ratio is low or the individual shareholder ratio is high and the most advanced technologies are not fully utilized to reflect information into stock prices, processing costs may remain relatively high, leading to the existence of PEAD.¹²

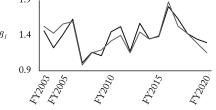
¹² To test the effects of technological development on PEAD more directly, I examine whether the decrease in PEAD is large, especially after the introduction of XBRL and Arrowhead, by extending Table 2. The unreported findings, however, do not show that their introductions are the main drivers of the decreasing trend of PEAD. One possible reason for these inconsistent results can be the influence of technologies other than XBRL and Arrowhead. If sophisticated investors have already used cutting-edge technologies before the introduction of XBRL and Arrowhead, their introductions might not have accelerated the decline in PEAD. In short, while the results do not indicate that

FIGURE 3. POST-EARNINGS ANNOUNCEMENT DRIFT: REGRESSION RESULTS Panel A: Full Sample



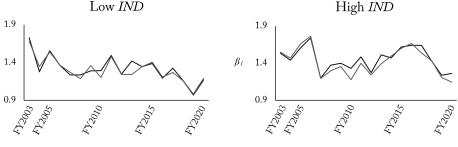






Panel C: Individual Ownership (IND) Low IND

βı



---- Market Model ----- Four-Factor Model

Notes: The figure displays the regression results of equation (1). Panel A shows the estimated β_1 for each fiscal year in the full sample. Panels B and C report the results of the subsample analysis. Panel B illustrates the estimated β_1 for the point of the 20th percentile of foreign ownership, and Panel C shows the results for the point of the 80th percentile of individual ownership each fiscal year. Please see the definitions of variables in the Appendix B.

the introduction of XBRL and Arrowhead results in a decrease in PEAD, these findings do not necessarily deny the hypothesis of this study. This means that direct evidence regarding technological developments reducing PEAD when using two examples of technological developments in the stock exchange market cannot be obtained.

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Panel A: Market Model

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Dependent Variable = β_1	: <i>β</i> 1									
	(1) Ful	(1) Full sample	(2) High FOR	h FOR	(3) Lo	(3) $Low FOR$	(4) Lo	(4) $Low IND$	(5) Hig	(5) High IND
	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
Constant	1.503^{***}	0.075	1.534^{***}	0.075	1.304^{***}	0.105	1.492^{***}	0.086	1.510^{***}	0.074
T	-0.016**	0.006	-0.020***	0.007	0.009	0.009	-0.018^{**}	0.007	-0.006	0.007
SE adjustment	Ro	Robust	Robust	ust	Roi	Robust	Rot	Robust	Roh	Robust
N	. –	18	18	8	1	18	1	18	1	18
$Adj-R^2$	0.	0.288	0.394	94	-0.	-0.007	0.3	0.305	-0.	-0.013
Panel B: Factor Model	ndel									
Dependent Variable = β_1	= β ₁									
	(1) Ful	(1) Full sample	(2) High FOR	h FOR	(3) Lo	(3) $Low FOR$	(4) Lo	(4) $Low IND$	(5) Hig	(5) High IND
	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
Constant	1.501^{***}	0.066	1.513^{***}	0.065	1.383***	0.104	1.491^{***}	0.071	1.515^{***}	0.088

Notes: The table presents the regression results of β_1 on T. Column (1) shows the results for the full sample, while columns (2)–(5) report the results of the subsample analysis. Columns (2) and (3) report the regressed results separately at the point of the twentieth percentage point of FOR each fiscal year. Columns (4) and (5) present the regressed results separately at the eightieth percentage point of IND each fiscal year. The White's standard error is used; ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed *t*-test. Please see the definitions of variables in the Appendix B.

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6. Robustness Analysis

6.1. Change in the Cut-off Points

In the primary analysis, the twentieth or eightieth percentage point is utilized as the shareholding ratio cut-off. In this section, a similar analysis is conducted using different cut-offs, namely the thirtieth or the seventieth percentage point and the fiftieth percentage points, to determine the initial results change.

Panels A and B of Table 3 show the same analysis results as the market model in Table 2 but with different cut-offs for the shareholding ratio, namely the thirtieth or the seventieth percentage points and the fiftieth percentage point. Similar to the findings of Table 2, the results indicate that PEAD decreases in subsamples with a low and high proportion of foreign and individual investors, respectively. This implies that the results of the primary analysis are independent of the ownership split.

6.2. PEAD Using Earnings Surprise and Forecast Innovation

The primary analysis employs the abnormal return on the earnings announcement day as a measure of news surprises to test the hypothesis that technological progress mitigates underreaction to unexpected news surprises. This is because the study focuses on the ability to integrate fundamental information including non-earnings information, which appears to have a high cost of information processing. However, PEAD literature focuses on a specific accounting item (particularly earnings), which is believed to require less processing cost. This section examines whether underreaction to a specific item surprise is also mitigated and determines whether the reduction in underreaction can be detected at varying levels of processing cost.

TSE requires all listed firms to report quarterly condensed financial reports (*Kessan-Tanshin*) that include key current financial items and management forecasts for the upcoming year. Although the disclosure of management forecasts is voluntary, most companies typically provide them (effectively mandated). Managers usually forecast the upcoming year's sales, operating income, ordinary income, net income, and earnings per share on *Kessan-Tanshin*. Most forecasts are point estimates with only a few range estimates. Additionally, TSE establishes a "significance rule" that requires managers to revise their most recent forecasts when significant changes occur. For instance, if the newly calculated net income forecast differs from the most recent publication by more than 30 percent, managers must revise it.

The central topics regarding this system are the credibility and usefulness of management forecasts. According to Kato et al. (2009), managers exhibit opportunistic bias by providing upward forecasts and later revise downward during the fiscal year. Owing to such downward revisions, the difference between actual earnings and the most recent forecasts is typically non-negative. Moreover, Ota (2011) identifies systematic bias in management forecasts and reveals that forecast errors are associated with financial distress, firm growth, firm size, and prior forecast errors.

Despite concerns regarding their credibility, prior studies reveal that management forecasts play an important role in the Japanese stock market. For example, Kato et al. (2009) confirm that stock prices react to the initial management forecasts and conclude that they are informative despite their inherent bias. Ota (2010) relies on value relevance research and demonstrates that management forecasts have the highest correlation and incremental explanation power with stock. Furthermore, he clarifies that more than 90 percent of changes in analysts' forecasts are solely explained by management forecasts.

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Panel A: The 30th or 70th Percentile

Dependent Variable = β_i								
	(1) Hig	$\operatorname{High}FOR$	(2) Lov	(2) $Low FOR$	(3) Low IND	N IND	(4) Hig	(4) High IND
	Coef.	Std. error	Coef.	Coef. Std. error	Coef.	Coef. Std. error	Coef.	Coef. Std. error
Constant	1.535^{***}	0.072	1.355^{***}	0.111	1.477*** 0.083	0.083	1.522^{***}	0.082
T	-0.021***	0.006	0.007	0.011	-0.018** 0.007	0.007	-0.009	0.008
SE adjustment	Rot	Robust	Roł	Robust	Robust	oust	Rol	Robust
Z	1	18	1	18	18	8	1	18
Adj-R ²	0.440	140	-0.	-0.032	0.328	28	0.0	0.024

Panel B: The 50th Percentile

Dependent Variable = β_I								
	(1) Hig	1) High <i>FOR</i>	(2) Lo ^x	(2) Low FOR	(3) Low IND	v IND	(4) High IND	h IND
	Coef.	Std. error	Coef.	Coef. Std. error	Coef.	Coef. Std. error	Coef.	Std. error
Constant	1.502^{***}	0.067	1.480^{***}	0.091	1.434^{***}	0.080	1.542^{***}	0.077
T	-0.024***	0.006	-0.002	0.008	-0.019^{**}	0.007	-0.012	0.007
SE adjustment	Roł	Robust	Rol	Robust	Robust	ust	Rot	Robust
Ν	1	18	1	18	18	8	1	18
Adj-R ²	0.6	0.605	-0.	-0.056	0.347	47	0.1	0.119

Notes: The table presents the regression results of β_I on T separately for High FOR (*IND*) and Low FOR (*IND*). Columns (1) and (2) present the regressed results separately at the point of the 70th percentile of IND each fiscal year. Panel B presents the results at the point of the 50th percentile of FOR and IND each fiscal year. White's standard error is used. ***, ***, and * indicate statistical significance of Panel A are the regressed results separately at the point of the 30th percentile of FOR each fiscal year. Models (3) and (4) of Panel A at the 1%, 5%, and 10% levels, respectively, using a two-tailed t-test. Please see the definitions of variables in the Appendix B. This empirical evidence indicates that both current earnings and management forecasts are essential in the Japanese stock market. This section confirms the underreaction to both current earnings and management forecast surprises. For current earnings surprises, I define them as the difference between actual earnings reported on the day of the earnings announcement and market expectation, which is typically estimated from the (1) previous year's earnings, (2) analysts' expected earnings, and (3) most recent management forecast. Previous years' earnings are called naive models, and analysts' expected earnings are typically used in the US. However, in Japan, where analyst coverage is low, most firms publish management forecasts; consequently, many studies use management forecast to estimate expected earnings and refers to the difference between actual earnings and management guidance as the "earnings surprise." For management forecast surprises, I define them, following Kato et al. (2009), as the difference between forecasted earnings for fiscal year t and refer to it as "forecast innovation."

This study assumes that information processing costs are high for all information on the earnings announcement date, management foretastes, and current earnings. The processing cost of all information on the date of earnings announcement is highest because it contains various financial items and non-financial information, though management forecast and current earnings are presented as single numeric values. The information processing cost for the management forecast is higher than that for current earnings because management forecasts have less credibility than actual earnings, and investors need information and analysis on how reliable the management forecasts are. For example, Kato et al. (2009) find that investors discount management forecasts issued by unreliable managers, and Ota (2011) reveals that analysts do not necessarily take management forecasts at face value. These findings imply that investors and analysts must invest time and effort to evaluate the reliability of information provided by management forecasts. In summary, I verify whether comparable results are obtained when using news surprises with varying levels of information processing costs compared to the primary analysis.

To examine the underreaction to earnings surprise and forecast innovation, I employ the following regression model:

- - -

$$AR_{i}^{2,60} = \beta_{0} + \beta_{1} T \times SUPC_{i,y} + \beta_{2} T \times SUPF_{i,y} + \Sigma Control Variables + \Sigma Firm Dummies + \Sigma Year Dummies + \varepsilon_{i,y}$$
(4),

where $AR_i^{2,60}$ is the firm *i*'s cumulative abnormal return from +2 to +60 days after the earnings announcement, $SUPC_{i,y}$ is the decile rank of the earnings surprise [(the current ordinary income – the most recent management forecast for the current ordinary income) / market capitalization] of firm *i* in fiscal year *y*, and $SUPF_{i,y}$ is the deciles rank of the forecast innovation [(management forecast for next year's ordinary income – the current ordinary income) / market capitalization] of firm *i* in fiscal year *y*. If underreactions to earnings surprise and forecast innovation are mitigated, both the coefficients of $T \times SUPC_{i,y}$, and $T \times SUPF_{i,y}$ should be negative.

As control variables, the model includes natural logarithms of market capitalization (lnMVE), natural logarithms of the difference between the fiscal year-end date and earnings announcement date (lnLAG), loss dummies (LOSS), number of firms announcing earnings on the same day (lnINT), stock beta (BETA), book-to-market ratio (BM), return on total assets (ROA), debt ratio (DEBT), total asset growth rate (GROWTH), stock volatility (RV) and accounting standard

dummy. Appendix B summarizes the definitions of these variables. The firm-year clustered standard errors are used.

Panel A of Table 4 shows the descriptive statistics. Both *SUPC* and *SUPF* range from 0 to 1 due to their rank-variable nature. Panel B reveals the correlation matrix. The correlation between *SUPF* and $AR^{2,60}$ is positive indicating market underreaction to forecast innovation. However, there is no positive correlation between *SUPC* and $AR^{2,60}$, which is inconsistent with underreaction.

Table 5 presents the regression results of equation (4). Column (1) represents the result for the full sample. Although the coefficient of forecast innovations (*SUPF*) is statistically significant, neither cross-term is significant. Columns (2) and (3) present the results for the foreign investors subsample, while columns (4) and (5) present the results for the individual investors subsample. The coefficients of earnings surprise (*SUPC*) or cross-term of earnings surprise and trend variable ($T \times SUPC$) are statistically non-significant in almost all columns. The forecast innovation (*SUPF*) coefficient is significantly positive across all columns, confirming that the market underreacts to forecast innovation. The cross-terms between forecast innovation and trend variable ($T \times SUPF$) are non-negative in the samples with Low *FOR* (column 3) and High *IND* (column 5), implying that PEAD does not decrease in the samples with low foreign investor ownership or high individual investor ownership. Conversely, the cross-terms between forecast innovation and the trend variable are negative in the samples with High *FOR* (column 2) or Low *IND* (column 4), which is consistent with the main analysis.

In conclusion, the results suggest that (1) there is no underreaction to earnings surprises in the Japanese market in the 21st century and (2) underreaction to forecast innovation is decreasing in the sample with high foreign investor ownership (low individual investor ownership). The first finding indicates that current earnings, which require the least amount of information processing, are immediately incorporated into stock prices on the day of the earnings announcement, and there is no drift in the 21st century. The second finding suggests that the underreaction is mitigated even at lower levels of information processing costs, which reinforces the primary findings.

Nevertheless, these findings may not be related to information processing costs. Even if there were no information processing costs, unreliable forecasts would still be discounted, and there would be an underreaction (Ng et al. 2013). For instance, if the management's earnings forecast for the upcoming year is 100, but investors deem it unreliable and overly optimistic, it might be interpreted as a discounted 70. When 100 is reported in the following year's earnings announcement, the stock price will reflect this value. Therefore, underreaction can occur even if there are no information processing costs. Consistent with this explanation, Ng et al. (2013) find that underreaction is greater when management forecasts are less reliable. Moreover, Atiase et al. (2005) discover that underreaction is greater with forecast innovations than earnings surprise, suggesting a strong preference for credibility. In short, the reasons for underreaction to less credible information include: (1) the time and effort required to evaluate the reliability of the information (it takes time to evaluate 70 when investors receive 100 from management forecast), and (2) the need to await the release of new information after considering all available information (after investors estimate 70, it takes time to get reliable information from the following year's earnings announcement). Thus, it is difficult to determine which path is responsible for the underreaction, and impossible to predict with certainty that the findings are related to information processing costs.

TABLE 4. DESCRIPTIVE STATISTICS AND CORRELATION MATRIX

	Ν	Mean	SD	P25	Median	P75
$AR^{2,60}$	50,510	0.196	17.656	-10.086	0.059	9.866
$AR^{-1,1}$	50,510	-0.049	6.294	-3.344	-0.167	2.929
SUPC	50,510	0.489	0.326	0.222	0.444	0.778
SUPF	46,252	0.500	0.319	0.222	0.444	0.778
Т	50,510	9.486	5.186	5.000	9.000	14.000
lnMVE	50,510	9.779	1.682	8.527	9.559	10.816
lnLAG	50,510	3.719	0.203	3.664	3.761	3.807
LOSS	50,510	0.132	0.339	0.000	0.000	0.000
lnINT	50,510	5.022	1.280	4.290	5.407	5.974
BETA	50,510	0.619	0.371	0.325	0.605	0.883
BM	50,510	1.173	0.758	0.618	1.015	1.541
ROA	50,510	0.053	0.054	0.024	0.046	0.078
DEBT	50,510	0.191	0.175	0.031	0.150	0.309
GROWTH	50,510	0.037	0.123	-0.024	0.023	0.078
RV	50,510	2.364	1.017	1.651	2.161	2.850
AVAR	50,510	2.960	5.407	0.151	0.831	3.177
AR^{pre}	46,175	0.443	9.718	-4.992	0.015	5.043
IEARN	46,175	0.101	0.104	0.057	0.100	0.151
RET	46,175	0.028	0.357	-0.175	0.025	0.229

Panel A: Descriptive Statistics

(continued on next page)

		7	2	3	4	5	9	7	8	6	10	11	12	13	14	15	16
-	AR ^{2,60}	1	0.141^{*}	-0.052*	-0.025*	0.076*	-0.034*	-0.127*	0.073*	0.019^{*}	-0.040*	-0.155*	0.156^{*}	-0.045*	-0.016^{*}	-0.108^{*}	-0.101^{*}
2	$AR^{-1,1}$	0.134^{*}	1	0.018^{*}	0.067*	0.300^{*}	-0.052*	0.044^{*}	0.018^{*}	0.006	-0.062*	-0.045*	0.048^{*}	-0.010*	0.000	-0.018*	-0.078
3	AVAR	-0.014^{*}	0.162^{*}	1	0.059*	-0.024*	0.125^{*}	0.182^{*}	-0.094*	-0.095*	0.008	0.165^{*}	-0.063*	0.154^{*}	-0.029*	0.107^{*}	-0.058*
4	SUPC	-0.025*	0.065*	0.046^{*}	1	-0.235*	0.002	0.112^{*}	-0.106^{*}	-0.057*	0.020^{*}	0.075*	-0.006	0.157^{*}	-0.025*	0.080^{*}	-0.009
ŝ	SUPF	0.085^{*}	0.302^{*}	0.017^{*}	-0.236*	1	0.000	-0.174^{*}	0.355^{*}	0.048^{*}	-0.022*	-0.012*	0.006	-0.351^{*}	0.163^{*}	-0.091^{*}	0.105^{*}
9	T	-0.043*	-0.045*	0.112^{*}	0.004	0	1	0.051^{*}	-0.086	-0.387*	0.288^{*}	0.190^{*}	-0.023*	0.089*	-0.076	0.129^{*}	-0.173*
7	InMVE	-0.115^{*}	0.039^{*}	0.123^{*}	0.114^{*}	-0.170^{*}	0.057*	1	-0.206*	-0.259*	-0.025*	0.440^{*}	-0.392*	0.310^{*}	-0.096	0.178^{*}	-0.221*
8	InLAG	0.013^{*}	-0.013*	-0.057*	-0.061*	0.051^{*}	-0.208*	-0.260*	1	0.129^{*}	0.002	-0.022*	0.090^{*}	-0.503*	0.141^{*}	-0.312*	0.191^{*}
6	SSOT	0.082^{*}	0.015^{*}	-0.065*	-0.110^{*}	0.355*	-0.078*	-0.192^{*}	0.099*	1	0.009*	-0.179*	0.084^{*}	-0.206^{*}	0.140^{*}	-0.117^{*}	0.133^{*}
10	lnINT	-0.044*	-0.062*	-0.003	0.029^{*}	-0.034*	0.214^{*}	0.011^{*}	0.075*	-0.009	1	0.095*	0.129^{*}	-0.089*	0.015*	-0.031^{*}	0.002
11	BETA	-0.128^{*}	-0.027^{*}	0.087*	0.071^{*}	-0.009*	0.232*	0.396^{*}	-0.144^{*}	-0.015^{*}	0.097*	1	-0.274*	0.097*	0.069^{*}	0.097*	0.387*
12	BM	0.161^{*}	0.044^{*}	-0.045*	-0.018^{*}	0.030^{*}	-0.030*	-0.392*	0.100^{*}	0.116^{*}	0.095*	-0.255*	1	-0.383*	-0.083*	-0.285^{*}	-0.101^{*}
13	ROA	-0.044	0.012^{*}	0.101^{*}	0.132^{*}	-0.307*	0.064*	0.257*	-0.153*	-0.497	-0.082*	0.075*	-0.334*	1	-0.352*	0.411^{*}	-0.101*
14	DEBT	-0.006	0.008	-0.028*	-0.031*	0.166^{*}	-0.082*	-0.083*	0.122^{*}	0.155^{*}	0.003	0.050*	-0.098	-0.308*	1	-0.089	0.154^{*}
15	GROWTH	-0.080*	-0.009*	0.061^{*}	0.053*	-0.039*	0.068*	0.118^{*}	-0.044*	-0.246*	-0.044*	0.092*	-0.256*	0.323^{*}	-0.013^{*}	1	-0.057*
16	RV	-0.079*	-0.068*	-0.105^{*}	-0.031^{*}	0.118^{*}	-0.135^{*}	-0.249*	0.106^{*}	0.220^{*}	-0.007	0.366^{*}	-0.081^{*}	-0.121^{*}	0.152^{*}	0.012^{*}	1

the bottom-left triangular matrix is the Pearson correlation. * indicates statistical significance at a less than 0.05 level of significance using a two-tailed *t*-test. Please see the definitions of variables in the Appendix B.

TABLE 4. (continued)

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Dependent Variable = $AR_{i}^{2,60}$

	(1) Full	(1) Full Sample	(2) High FOR	h FOR	(3) Lo	(3) Low FOR	(4) Lo	(4) $Low IND$	(5) Hi _£	(5) High IND
	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
SUPC	0.553	0.913	0.976*	0.561	-2.067	1.346	0.889	0.930	-0.409	1.284
SUPF	4.840****	1.509	5.958***	0.627	2.656^{*}	1.452	5.041***	1.663	4.120^{**}	1.634
$T \times SUPC$	-0.036	0.073	-0.063	0.055	0.127	0.133	-0.068	0.080	0.039	0.113
$T \times SUPF$	-0.125	0.141	-0.254***	0.059	0.081	0.168	-0.163	0.157	0.148	0.162
Control	Y	Yes	Yes	SS	Υ	Yes	Y	Yes	Υ	Yes
Firm	Υ	Yes	Yes	SS	Y	Yes	Y	Yes	Υ	Yes
Year	Υ	Yes	Yes	SS	Υ	Yes	Υ	Yes	Υ	Yes
SE adjustment	Firm-year	Firm-year-clustered	Firm-year-clustered	-clustered	Firm-yea	Firm-year-clustered	Firm-yea	Firm-year-clustered	Firm-year	Firm-year-clustered
Z	45,	45,942	36,973	773	8,	8,495	38,	38,078	7,5	7,550
Adj-R ²	0.2	0.250	0.244	44	0	0.326	0.2	0.249	0.2	0.267

year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed *t*-test. Please see the and (5) show the results of equation (4) separately at the 80th percentile point of IND each fiscal year. Control variables include t_{nMVE} , InLAG, LOSS, InINT, BETA, BM, ROA, DEBT, GROWTH, RV, and accounting standard dummy. Standard errors are clustered by firm-Columns (2) and (3) show the results of equation (4) separately at the 20th percentile point of FOR each fiscal year, and columns (4) definitions of variables in the Appendix B.

7. Additional Analysis

7.1. Abnormal Return Variance and PEAD

Underreaction to earnings announcements on the Japanese stock market has decreased in the 21st century (Section 5). If the information released on earnings announcement dates remains constant, the underreaction mitigation should lead to an increase in the stock price reaction to earnings announcements. To supplement and bolster the credibility of the primary empirical findings, this section conducts additional analyses regarding stock price reactions on the date of earnings announcements.

Several studies have attempted to explain the increase in price response to earnings announcements in the US and Japan (Beaver et al. 2018; Jinushi 2022). Beaver et al. (2020) investigate whether management guidance or analyst forecasts bundled with earnings announcements are a possible cause, given the increase in such bundled earnings announcements, and find that this cannot fully explain the phenomenon. Other studies consider not only the change in the contents of earnings announcements but also the influence of investors. Thomas et al. (2022) incorporate findings from the finance literature. They demonstrate that the measurement of price response to earnings announcements used by Beaver et al. (2018) is influenced by the amount of information during the non-earnings announcement period, microstructure noise, and market efficiency. Lee and Watts (2021) observe that the increase may be partially explained by algorithmic trading at the time of earnings announcement, and it does not necessarily indicate an increase in the contents of earnings announcement information.

This section investigates whether the evolution of information technology has mitigated the underreaction by increasing the stock price reaction on the date of earnings announcements. Specifically, I examine if the reaction to earnings announcements is increasing in samples with high levels of foreign ownership or low levels of individual investor ownership, where I observed a reduction in PEAD in the primary analysis.

To measure the price reaction to earnings announcements, I use *AVAR* as a measure following prior research (Beaver et al. 2018, 2020). *AVAR* is calculated as the square of the three-day cumulative abnormal returns in the earnings-announcement window divided by the variance of the three-day cumulative abnormal returns in the non-earnings-announcement window. The following model is estimated separately for firms with low foreign and high individual ownership:

$$AVAR_{i,v} = \gamma_0 + \gamma_1 T_v + \Sigma Control Variables + \Sigma Firm Dummies + \varepsilon_{i,v}$$
 (5),

where AVAR is the dependent variable, and T is the independent variable. Control variables include natural logarithmic value of market value (lnMVE), natural logarithms of the difference between the fiscal year-end date and earnings announcement date (lnLAG), loss dummy (LOSS), natural logarithmic value of the number of firms releasing earnings announcements on the same day (lnINT), stock beta (BETA), book-to-market ratio (BM), return on assets (ROA), debt ratio (DEBT), total asset growth rate (GROWYH), the absolute value of earnings surprise scaled by market value (|SUPC|), absolute value of forecast innovation scaled by market value (|SUPF|), and accounting standard dummies. The firm-year clustered standard error is used.

Table 6 displays the regression results. Column (1) represents the full sample, columns (2) and (3) are the subsample of foreign investors, and columns (4) and (5) represent the subsample of individual investors. The T coefficient is significantly positive in the full sample analysis in column

Dependent Variable = <i>AVAR</i>	AVAR				
	(1) Full Sample	(2) High FOR	(3) $Low FOR$	(4) $Low IND$	(5) High IND
	Coef. Std. error	Coef. Std. error	Coef. Std. error	Coef. Std. error	Coef. Std. error
T	0.115*** 0.025	0.138*** 0.031	0.018 0.015	0.128**** 0.026	0.042 0.026
Control	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes
SE adjustment	Firm-year-clustered	Firm-year-clustered	Firm-year-clustered	Firm-year-clustered	Firm-year-clustered
Z	46,600	37,504	8,613	38,562	7,731
Adj - R^2	0.080	0.071	0.078	0.082	0.081
Notes: The tal: (3) show the ru	le reports the results of th egression results separatel	ne regression of AVAR on y at the 20 th percentile po	$N_{\theta \ell S t}$: The table reports the results of the regression of $AVAR$ on T . Column (1) presents the result of the full sample, columns (2) and (3) show the regression results separately at the 20^{th} percentile point of FOR each fiscal year, and columns (4) and (5) present the results of the 80^{th} becomes at the 80^{th} becomes a the 80^{th} becomes a the 100^{th} becomes a the 10^{th} be	he result of the full sample ; and columns (4) and (5) (C) TOSS <i>I</i> TNT RETA	e, columns (2) and present the results RM ROA DFRT

TABLE 6. PRICE RESPONSE TO EARNINGS ANNOUNCEMENT

at the 80th percentile point of *IND* each fiscal year. Control variables include *mMVE*, *mLAG*), *LOSS*, *mINT*, *BETA*, *BM*, *KOA*, *DEBT*, GROWTH, RV, |SUPC|, |SUPF| and the accounting standard dummies. Standard errors are clustered by firm-year.***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed t-test. Please see the definitions of variables in the Appendix B. (1), confirming that the stock price responsiveness increases on the day of the earnings announcement. However, the T coefficient is statistically non-significant in the subsamples of Low *FOR* in column (3) and High *IND* in column (5), where no decrease in PEAD is observed. These results suggest that the development of information technology increases the responsiveness of stock prices on the day of the earnings announcement, thereby mitigating underreaction.

7.2. Impact of Regulation Fair Disclosure

This section examines the impact of the regulation fair disclosure, which was enacted in 2006. The regulation requires firms to provide the same information to the general public simultaneously if they provide private information to certain analysts. This regulation may have affected PEAD by decreasing the amount of information disclosed before the earnings announcement date, thereby increasing the amount of information disclosed on the day of the earnings announcement. Owing to investors' limited information processing capacity, the increase in new information released on the day of earnings announcements may make it impossible to process all information immediately. Thus, implementing the regulation fair disclosure may lead to an increase in PEAD.

To examine the change in PEAD after the introduction of the regulation fair disclosure, I conduct several analyses. First, a price-leads-earnings analysis is conducted (Arif et al. 2019). The following equation is estimated separately, before and after FD.

$$SUPC_{i,y} \text{ or } SUPF_{i,y} = \beta_0 + \beta_1 A R_{i,y}^{pre} + \Sigma \text{ Control Variables} + \Sigma \text{ Firm Dummies} + \Sigma \text{ Year Dummies} + \varepsilon_{i,y}$$
(6).

Following Horie and Kagaya (2021), the fiscal year ending between April 2014 and March 2016 (fiscal year 2015 and 2016) are considered as *Before FD*, and the fiscal year ending between April 2017 and March 2019 (fiscal year 2018 and 2019) are considered as *After FD*. $AR_{i,y}^{pre}$ is the firm *i*'s cumulative abnormal return from the end of the fiscal year to the date of earnings announcement in fiscal year y. Control variables include lag of earnings (*IEARN*), returns over the fiscal year (*RET*), cumulative abnormal return from +2 to +60 business days after the earnings announcement ($AR^{2,60}$), and cumulative abnormal return from -1 to 1 around the earnings announcement ($AR^{-1,1}$).

Next, to measure both of the price reaction and the underreaction to earnings surprise, the following equation is estimated separately, before and after FD.

$$AR_{i,y}^{-1,1} \text{ or } AR_{i,y}^{2,60} = \beta_0 + \beta_1 SUPC_{i,y} + \beta_2 SUPF_{i,y} + \Sigma \text{ Control Variables} + \Sigma \text{ Firm Dummies} + \Sigma \text{ Year Dummies} + \varepsilon_{i,y}$$
(7).

Control variables include natural logarithmic value of market value (lnMVE), natural logarithms of the difference between the fiscal year-end date and earnings announcement date (lnLAG), loss dummy (LOSS), natural logarithmic value of the number of firms releasing earnings announcements on the same day (lnINT), stock beta (BETA), book-to-market ratio (BM), return on assets (ROA), debt ratio (DEBT), total asset growth rate (GROWYH), return volatility (RV), and accounting standard dummies. The firm-year clustered standard error is used.

Panel A of Table 7 displays the regression results. Column (1) presents the results of the realized earnings surprise, whereas column (2) shows the results of the forecast innovation. In

column (1), the coefficient of AR^{pre} is significantly positive *Before FD*, indicating that information regarding earnings surprises is incorporated beforehand. However, AR^{pre} becomes non-significant *After FD*, suggesting that information is no longer incorporated. In Column (2), the AR^{pre} coefficients are insignificant, indicating that management-forecast information is not incorporated into stock prices before the earnings announcement. Panel B of Table 7 shows the results for both the responses and PEAD for earnings surprise and forecast innovation. Column (1) compares the stock price responsiveness to earnings surprises *Before FD* and *After FD*. The coefficients of *SUPC* and *SUPF* increase from 2.584 to 4.127 and 8.538 to 10.177, respectively, indicating that the stock price responsiveness to earnings surprises increases *After FD*. Column (2) compares PEAD *Before FD* and *After FD*. The coefficients of *SUPC* and *SUPF* increase from -0.313 to 1.094 and 2.215 to 3.614, respectively, but they are statistically non-significant.

Therefore, the results indicate that although the amount of information incorporated into the stock price before the earnings announcement decreases slightly after the regulation fair disclosure, the increase in the price response to earnings announcements is likely to prevent the increase in PEAD. This suggests that the regulation fair disclosure has a non-significant influence on the main findings of this study.

8. Conclusion

Since Ball and Brown's (1968), technological advancements have revolutionized the stock market by enabling investors to process information from earnings announcements more efficiently. This study aims to determine whether PEAD exists in the Japanese stock market in the 21st century.

Using Japanese data, this study finds that PEAD has decreased during the sample period, except for earnings announcements of firms with a low level of foreign investor ownership or high level of individual investor ownership. This suggests that, in such subsamples, the latest technologies may not be fully utilized to incorporate information into stock prices, and processing costs may remain high. Moreover, these changes in investor trading styles can be attributed to the acceleration of the price response to earnings announcements.

However, this study has some limitations. First, it is unclear whether the disappearance of PEAD is a permanent or temporary trend. Second, the assumption that the shareholdings ratio of foreign investors (individual investors) is correlated with the trading volume (in JPY) on the earnings announcement date may not be accurate. Future studies should employ more sophisticated measurement techniques to verify this assumption, such as directly measuring trading volume (in JPY) using investors' account data. Third, this study does not fully eliminate the possibilities of alternative interpretations. It uses ownership structure as a proxy for the development of information technology; however, it is an indirect measure. Ownership structure may be a proxy for other factors, and future studies should examine this issue using more direct data on information technology.

		(1) Dependent Variable = <i>SUPC</i>	(2) Dependent	(2) Dependent Variable = $SUPF$
T.	Before FD	After FD	Before FD	After FD
1	(FY 2015-FY 2016)	(FY 2018–FY 2019)	(FY 2015–FY 2016)	(FY 2018–FY 2019)
	Coef. Std. error	Coef. Std. error	Coef. Std. error	Coef. Std. error
AR ^{pre} 0.	0.003* 0.001	0.002 0.001	0.001 0.001	0.001 0.001
Control	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
SE adjustment Fi	Firm-year-clustered	Firm-year-clustered	Firm-year-clustered	Firm-year-clustered
N	4,648	4,550	4,490	4,366
Adj-R ²	0.140	0.231	0.420	0.384

TABLE 7. RESULTS OF REGULATION FAIR DISCLOSURE

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Panel B: Response to Earnings Announcement and Post Earnings Announcement Drift

	(1) De	spendent Va	1) Dependent Variable = $AR^{-1,1}$	Ľ		(2) Dependent Variable = $AR^{2,60}$	Variable = <i>AR</i>	2,60
	Before FD		After FD	FD	Befor	Before FD	Afte	After FD
	(FY 2015–FY 2016)	2016)	(FY 2018–FY 2019)	FY 2019)	(FY 2015-	(FY 2015-FY 2016)	(FY 2018	(FY 2018–FY 2019)
	Coef. Std	Std. error	Coef.	Std. error	Coef.	Std. error	Coef.	Std. error
SUPC	2.584* 0	0.391	4.127*	0.423	-0.313	0.810	1.094	0.800
SUPF	8.538** 0	0.567	10.177^{**}	0.524	2.215	1.106	3.614	1.250
Control	Yes		Yes	Ş	Y	Yes	Υ	Yes
Firm	Yes		Yes	Ş	Y	Yes	Υ	Yes
Year	Yes		Yes	Ş	Y	Yes	Υ	Yes
SE adjustment	Firm-year-clustered	stered	Firm-year-clustered	clustered	Firm-yea	Firm-year-clustered	Firm-yea	Firm-year-clustered
N	4,920		4,832	32	2,4	4,920	4,	4,832
Adj-R ²	0.216		0.199	66	0.2	0.246	0.	0.205
<i>Notes</i> : The table F include <i>IEARN</i> , . shows the results <i>BM</i> , <i>ROA</i> , <i>DEB</i>	<i>Notes</i> : The table presents the results of the regulation FD analysis. Panel A shows the regression results of equation (6). Control variables include <i>IEARN</i> , <i>RET</i> , <i>AR</i> ^{2,60} , <i>AR</i> ^{-1,1} , and the accounting standard. Panel B shows the regression results of equation (7). Column (1) shows the results of AR ^{-1,1} , and column (2) presents the results of <i>AR</i> ^{2,60} . Control variables include <i>InMVE</i> , <i>InLAG</i> , <i>LOSS</i> , <i>InINT</i> , <i>BETA</i> , <i>BM</i> , <i>ROA</i> , <i>DEBT</i> , <i>GROWTH</i> , <i>RV</i> , and accounting standard dummy. Standard errors are clustered by firm-year. ***, ***, and * indicate	of the regular , and the aco nn (2) presen and account.	tion FD analys counting stanc ats the results (ing standard d	is. Panel A shows lard. Panel B sho of AR ^{2,60} . Control ummy. Standard	the regression re ws the regressio variables include errors are cluste	esults of equation on results of equ e <i>lnMVE</i> , <i>lnLAC</i> red by firm-year	n (6). Control v ation (7). Col <i>3</i> , <i>LOSS</i> , <i>InINT</i> r. ***, **, and *	/ariables umn (1) , <i>BETA</i> , indicate

statistical significance at the 1%, 5%, and 10% levels, respectively, using a two-tailed t-test. Please see the definitions of variables in the

Appendix B.

Appendix A: Carhart Four-Factor Model

This study obtains factor returns from Kenneth French's data library, commonly used database for applying Fama–French factor models in empirical research. However, using downloaded factors without adjustments can pose a significant issue since these factors are provided in US dollars (Glück et al. 2021). To address this issue, I convert factor returns into Japanese yen (JPY).

Following Glück et al. (2021), the market premium and other premiums (HML, SMB, and MOM) are adjusted for currency fluctuations using the following formula.

Market premium:

$$MP_{t}^{JPY} = \frac{1}{(1 + r_{FX,t}^{USD/JPY})} (1 + MP_{t}^{USD} + r_{f,t}^{USD}) - 1 - r_{f,t}^{JPY},$$

Other premiums:

$$Premium_{t}^{JPY} = \frac{1}{(1 + r_{FX,t}^{USD/JPY})} Premium_{t}^{USD}$$

where MP_t^{JPY} is the market factor in JPY, MP_t^{USD} is the market factor in USD, $Premium_t^{JPY}$ is the other factor (e.g, HML, SMB, and MOM factors) in JPY, $Premium_t^{USD}$ is the other factor in USD, $r_{f,t}^{JPY}$ is the Japanese risk-free rate, $r_{f,t}^{USD}$ is the US risk-free rate, and $r_{FX,t}^{USD/JPY}$ is the discrete returns of the spot exchange rate between USD and JPY on day *t*. Data for MP_t^{USD} , $Premium_t^{USD}$, and $r_{f,t}^{USD}$ are obtained from Kenneth French's data library. The Japanese risk-free rate ($r_{f,t}^{JPY}$) is based on the interest rate for 10-year JGBs from the International Interest Rate Information published by the Ministry of Finance.¹³ The exchange rate ($r_{FX,t}^{USD/JPY}$) is obtained from the Bank of Japan's BOJ Time-Series Data Search.¹⁴

¹³ Data are available at: https://www.mof.go.jp/jgbs/reference/interest_rate/index.htm.

¹⁴ I obtained the Tokyo market dollar/yen spot as of 17:00 (FM08'FXERD04). Available at: https://www.statsearch.boj.or.jp/ssi/cgi-bin/famecgi2?cgi=\$nme_a000&lstSelection=FM08.

Variables	Definitions
FOR	 Percentage of shares held by foreign investors, defined as the number of shares held by foreign firms, etc. divided by the number of outstanding shares excluding the shares less than one unit at the fiscal year. High FOR (Low FOR) indicates the subsample where the level of FOR is above (below) the 20th percentile point.
IND	 Percentage of shares held by individual investors, defined as the number of shares held by individuals and others divided by the number of outstanding shares excluding the shares less than one unit at the fiscal year. High <i>INL</i> (Low <i>IND</i>) indicates the subsample where the level of <i>IND</i> is above (below) the 80th percentile point.
$AR^{k,l}$	= Cumulative abnormal return from k to l business days around the annua earnings announcement. Abnormal returns are calculated using the marke model or the Carhart four-factor model. The earnings announcement day is defined as the business day after the earnings announcement day in the database.
β_1	= Estimated coefficient from equation (1) for each fiscal year.
T	= Trend variable, which takes 1 if the fiscal year is 2003 and 2 if the fiscal year is 2004, and so on.
AVAR	= Abnormal return variance, defined as the square of the three-day cumulative abnormal return $(AR^{-1,1})$ around the earnings announcement divided by the variance of three-day cumulative abnormal returns in the non-earnings- announcement window. Abnormal returns are calculated using the marke model or the Carhart four-factor model.
AR^{pre}	 Cumulative abnormal return from the end of the fiscal year to the earning: announcement date. Abnormal returns are calculated from the market mode or Carhart four-factor model.
SUPC	Decile rank of an earnings surprise, defined as the difference between the current year's ordinary income and the latest management forecast for the current year's ordinary income deflated by the market value at the end of the fiscal year. To facilitate interpretation, the variable is converted to (decile rank - 1) / 9. The absolute value of SUPC is SUPC .
SUPF	 Decile rank of forecast innovation, which is defined as the difference betweer management forecast for next year's ordinary income and current year's ordinary income deflated by the market value at the end of the fiscal year. To facilitate interpretation, the value is converted to (decile rank - 1) / 9. The absolute value of SUPF is SUPF .
lnMVE	 Natural logarithm of the market value of equity at the end of the fiscal year The market value of equity equals the closing price times the share outstanding excluding treasury stock at the end of the fiscal year.

APPENDIX B: DEFINITIONS OF VARIABLES

lnLAG	=	Natural logarithm of the difference between the fiscal year-end date and the annual earnings announcement date.
LOSS	=	Loss dummy variable, which takes 1 when ordinary income is negative, and 0 otherwise.
lnINT	=	Natural logarithm of the number of firms that release quarterly, semi-annual, or annual <i>Kessan-Tanshin</i> on the same day as the firm announced annual <i>Kessan-Tanshin</i> .
BETA	=	The stock beta (γ_i) , which is estimated from equation (2)
BM	=	Book-to-market ratio. The book value of equity is the shareholders' equity at the end of the fiscal year. The market value of equity equals the closing price times the shares outstanding excluding treasury stock at the end of the fiscal year.
ROA	=	Return on assets, defined as ordinary income divided by total assets at the end of the fiscal year.
DEBT	=	Debt ratio for total assets, defined as interest-bearing debt (short-term debt + long-term debt, corporate bond and lease obligations in the current liabilities + long-term debt, corporate bond and lease obligations in the long-term liabilities) divided by total assets at the end of the fiscal year.
GROWTH	=	Growth rate of total assets, defined as (total assets _t - total assets _{t-1}) / total assets _{t-1} .
RV	=	Return volatility in the non-earnings-announcement window (from day –260 to day –3 relative to the annual earnings announcement date.
IEARN	=	Ordinary income in the previous year divided by the market value of equity at the end of the previous fiscal year.
RET	=	Stock price return over the fiscal year, defined as the difference between the closing price of the previous fiscal year and that of the current fiscal year, divided by the closing price of the previous fiscal year.

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