



Article **Private Information Production and the Efficiency of Intra-Industry Information Transfers**

Jingjing Xia 匝

College of Business and Public Management, Wenzhou-Kean University, Wenzhou 325015, China; jxia@kean.edu

Abstract: This paper challenges the prevailing view that intra-industry information transfers are primarily driven by public information. Contrary to conventional wisdom, I find that investors in late-announcing firms impound more private information after earlyannouncing peers report earnings. This increase is substantial, leading to an 18.2% decrease in analyst forecast consensus and a 24.9% increase in forecast precision. Moreover, the probability of informed trading rises by 2% on days with peer announcements. This finding is important because investors tend to overweight (underweight) private (public) signals, thereby exacerbating over- and underreaction anomalies. Our study confirms that these anomalies are more pronounced when early announcements stimulate private information production, offering a theoretical explanation for their puzzling coexistence. These findings have significant implications for investor behavior and market efficiency. Investors should diligently evaluate both public and private information, particularly following peer announcements. Policymakers can leverage these findings to design regulations that promote transparency and foster efficient information dissemination.

Keywords: intra-industry information transfer; private information production; overconfidence; market efficiency

JEL Classification: M40; M41; G10; G14

1. Introduction

The literature on intra-industry information transfers suggests that earnings announcements of one firm contain information relevant to other firms in the industry.¹ Thus, when early-announcing industry peers announce earnings, investors impound this public industry-wide information in late-announcing firms' prices (e.g., Hann et al., 2019; Liu et al., 2022). Although most of the studies in this area assume that information transfers involve primarily public information, little research has been conducted to empirically validate this assumption. This gap in the literature hinders our understanding of information processing by investors within the dynamic context of sequential earnings announcements, and the implications of such behavior for market efficiency. Specifically, it leaves open the question of whether investors appropriately weight public and private information signals when reacting to peer announcements, with potential implications for the overand underreaction anomalies observed in prior research. This paper aims to fill this void by providing empirical evidence on the nature of the information that investors generate when peers announce earnings, and examining its effects on the efficiency of intra-industry information transfers.

A long stream of research finds that earnings information of industry peers contains a common component, which is useful for investors to update their expectations about



Academic Editor: Thanasis Stengos

Received: 15 December 2024 Revised: 10 January 2025 Accepted: 13 January 2025 Published: 20 January 2025

Citation: Xia, J. (2025). Private Information Production and the Efficiency of Intra-Industry Information Transfers. *Journal of Risk and Financial Management*, *18*(1), 42. https://doi.org/10.3390/ jrfm18010042

Copyright: © 2025 by the author. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/ licenses/by/4.0/). the earnings of late-announcing firms (e.g., Hann et al., 2019; Liu et al., 2022). However, information transfers may not necessarily involve only public information, as market participants may also generate private information when learning from the peers' earnings. For example, investors may have idiosyncratic interpretations of the peers' news due to different knowledge sets or prior beliefs. They may also be incentivized to seek additional information that can be used in conjunction with the peers' public announcements to better gauge the value of the firm (e.g., Barron et al., 2002; Barron et al., 2005; Dyer, 2021; Crane et al., 2023).² Despite of this possibility, the extant research has been largely silent on whether industry peers' earnings announcements can serve as a "trigger" for more private information production by late-announcing firms' investors.

Understanding the type of information that investors generate when industry peers announce earnings is important, as it may have implications for the efficiency of information transfers. The distinction between private and public information is particularly important in this context because if investors primarily rely on public information, I would expect efficient market responses where prices quickly and accurately reflect new information from the peers. However, if private information plays a significant role, it can lead to behavioral biases and deviations from market efficiency. This is because private information is often subject to greater interpretation and may be influenced by individual investor beliefs, potentially leading to over- or underreactions (e.g., Daniel et al., 1998).

Previous studies have documented a puzzling coexistence of both over- and underreactions by late-announcing firms' investors to early-announcing peers' earnings announcements. Specifically, the overreaction anomaly refers to a significantly negative relationship between a late-announcing firm's excess returns on the early-announcing peers' announcement days and its excess return on its own earnings announcement later in the quarter (Thomas & Zhang, 2008). Conversely, the underreaction anomaly refers to a significantly positive relationship between the early-announcing peers' own announcement excess returns and the late-announcing firm's own announcement excess returns (Ramnath, 2002; Thomas & Zhang, 2008).

Thomas and Zhang (2008) propose that these seemingly contradictory findings arise because information in early announcers' news has two components: one with implications for future quarters and another relevant only to the current quarter. They argue that overreaction stems from investors overemphasizing the current-quarter information due to the representativeness heuristic, while underreaction results from underweighting the time-series implications of peer earnings. However, they acknowledge the need for further research to fully explain these inefficiencies. Ramnath (2002) offers no specific explanation, simply attributing underreaction to a general investor tendency to underreact to public information.

Evidence on late-announcing firm investors' private information production in information transfers may shed new light on this puzzle, since a large body of research shows that investors tend to overestimate (underestimate) the precision of private (public) information signals due to overconfidence (e.g., Daniel et al., 1998; Chou et al., 2021). To the extent that investors of late-announcing firms engage in more private information production when peers announce earnings, they may place a higher weight on information with which they have more personal involvement and less weight on the peers' public earnings announcements. Consequently, they may overreact to the private information produced on the peers' earnings announcement days when updating their expectations about the late-announcing firms' (yet-to-be-announced) earnings, leading to a negative relationship between the firm's excess returns on the early-announcing peers' announcement days and its own announcement returns (Thomas & Zhang, 2008). At the same time, investors may underreact to industry peers' public earnings reports, resulting in a positive relationship between the peers' announcement of excess returns and the late-announcing firms' announcement of excess returns (Ramnath, 2002; Thomas & Zhang, 2008).

I test whether early-announcing peers' earnings announcements stimulate more private information production by late-announcing firm investors and its implications for the mispricing in information transfers using a sample of firm earnings announcements from 2003 to 2021. I use two measures of private information production. The first one is based on analysts' earnings forecasts. Specifically, I follow the methodology described in Barron et al. (2002) and examine the change (if any) in the proportion of common information relative to total information and the precision of the analysts' private information in their current-quarter earnings forecasts about a late-announcing firm after industry peers begin to announce earnings for the same quarter.³ As shown in Figure 1a, I found that the analyst forecast consensus (precision) decreases (increases) by 18.2% (24.9%) after the first industry peer's earnings announcement in the season. To the extent that analysts are a reasonable proxy for investors (e.g., Hossain et al., 2019; Balakrishnan et al., 2021), these results lend support to the conjecture that investors engage in more private information production when peers announce earnings.



Figure 1. Private information production and industry peer earnings announcements. Figure 1 plots the change in private information production about the late-announcing firm when early-announcing industry peers report earnings, based on the statistics reported in Table 1. Specifically, (**a**) plots the average change in analyst forecast consensus (CONSENSUS) and precision (PRECISION) after the first earnings announcement by an industry peer in the earnings season; and (**b**) plots the average change in the late-announcing firm's probability of informed trading (PIN) on days with early-announcing industry peers' earnings announcements and days without such announcements.

To address the concern that not all analysts choose to revise their forecasts after industry peers announce earnings, the second measure I use is the investor-based probability of informed trading (PIN) (e.g., Easley et al., 2002). In each year, I estimate the PIN of a particular firm separately on days when early-announcing industry peers report earnings and on days when no peers report earnings, and compare the firm's PIN calculated using these two sets of days.⁴ As illustrated in Figure 1b, empirical results suggest that the late announcers' PIN on days when early announcers report earnings is 2% higher than that on days when no peers report earnings. Collectively, these findings imply that private information production actually dominates the impounding of public information by late-announcing firm investors in intra-industry information transfers.

Next, I investigate whether the heightened private information production by lateannouncing firm investors on the early-announcing peers' earnings announcement days can explain the co-existence of the over- and underreaction anomalies. Specifically, I hypothesize that both over- and underreactions should be stronger when the peers' announcements trigger more private information production, as measured by a greater increase in the amount of idiosyncratic information contained in analysts' forecasts for the late announcer after industry peers begin to report earnings, or when the late-announcing firms have a higher PIN when the early-announcing peers report earnings. These predictions are borne out in the data.

Table 1. Descriptive statistics.

Panel A. Firm-Quarter Observations						
	Mean	Std.	P75	Median	P25	Ν
PRE_CONSENSUS	0.516	0.439	0.908	0.649	0.147	53,425
POST_CONSENSUS	0.422	0.512	0.857	0.466	-0.191	53,425
PRE_PRECISION	2404.47	5388.65	907.48	109.33	9.44	53,425
POST_PRECISION	3004.38	7670.15	2106.88	219.85	19.47	53,425
LOG_NDAYS	4.317	0.659	4.684	4.425	4.048	53,425
Panel B. Firm-Year O	bservation	IS				
	Mean	Std.	P75	Median	P25	Ν
PIN_AD	0.256	0.094	0.303	0.252	0.192	10,430
PIN_NAD	0.249	0.092	0.288	0.250	0.192	10,430
ROA	0.003	0.137	0.061	0.020	0.003	10,430
LOGSIZE	6.143	1.815	7.319	6.025	4.810	10,430
LOGBM	-0.750	0.790	-0.230	-0.660	-1.180	10,430
LOGACOV	2.050	1.220	3.000	2.300	1.100	10,430
INSTOWN	0.407	0.341	0.723	0.381	0.039	10,430

Table 1 presents descriptive statistics for the main sample. All continuous variables are winsorized at 1% and 99% (except LOG_NDAYS, PIN_AD, PIN_NAD, LOGACOV and INSTOWN). All variables are defined in Appendix B.

In an additional analysis, I provide further evidence on this private-informationproduction explanation by considering two situations where late announcers' investors are more likely to generate private information based on the early announcers' earnings reports. As investors are more likely to collect private information when it is more profitable to do so (e.g., Bolandnazar et al., 2020), the first situation I identify is when the peers' earnings announcements are more relevant to the late-announcing firm, since, when combined with private information, the earnings news from the more relevant peers can better enable investors to infer its upcoming earnings announcement. To measure peer news relevance, I use the product similarity score developed in Hoberg and Phillips (2010, 2016) between the early and late announcer or the abnormal Electronic Data Gathering, Analysis, and Retrieval (EDGAR) search traffic for the late announcer on the early announcers' announcement days (e.g., Drake et al., 2015). Empirical evidence suggests that the overand underreactions are stronger when close product market peers announce earnings and when there is higher abnormal EDGAR search traffic for the late announcer when early announcers report earnings.

The second situation is when the early announcers' news has ambiguous implications for the late-announcing firm. For example, when all early announcers report positive (negative) news, the late-announcing firms are also likely to have positive (negative) news, since the consistency in the signs of the early announcers' news may indicate an industry trend. However, when some early-announcing peers report positive news while others have negative news, the sign of the late-announcing firm's earnings news will become more difficult to predict. Private information production is more likely when peers have mixed news because a late-announcing firm's announcement can resolve more uncertainty, making pre-announcement private information production more profitable (e.g., Bolandnazar et al., 2020). Furthermore, inferring late-announcing firms' earnings involves more judgment when early announcers report mixed news, leaving more room

for overconfidence to take effect (e.g., Daniel et al., 1998). To measure the early announcers' news ambiguity, I use either (the negative of) the absolute value of the difference between the percentage of positive and negative news from the early announcers or the dispersion of early announcers' news on a given day. The results support the prediction that both the over- and underreactions are more pronounced when the early announcers report mixed news.

This paper makes two contributions to the literature. First, it deepens our understanding of intra-industry information transfers by providing new insights into the nature of information (public versus private) that investors incorporate into late-announcing firms' prices following early-announcing peer earnings reports. While prior research emphasizes peer announcements as a source of public information for revising expectations about non-announcing firms, this study demonstrates that private information production dominates the incorporation of public information. This finding sheds new light on how peer earnings announcements stimulate investors' private information production activities in the equity market, challenging traditional assumptions about information processing in financial markets. This contribution builds upon the work of Drake et al. (2015), who showed that investor attention increases following peer earnings announcements, but did not explore the type of information investors gather. This study addresses this gap by examining whether investors primarily incorporate public or private information in response to peer announcements.

Second, this paper contributes to the literature on behavioral finance and market efficiency by offering a compelling explanation for the previously unresolved puzzle of coexisting over- and underreactions in information transfers. By establishing the dominance of private information production in response to peer announcements, this study provides a theoretical framework for understanding how investor overconfidence, coupled with the overweighting of private signals, can lead to these seemingly contradictory phenomena. This framework advances behavioral theories of investor behavior by highlighting the interplay of private information, overconfidence, and biased information processing in shaping market dynamics and contributing to market inefficiencies. This contribution also builds on prior work, specifically that of Thomas and Zhang (2008), who documented the puzzling coexistence of over- and underreactions but acknowledged the need for further research to fully understand these phenomena. This study delves deeper into the mechanisms driving these reactions, examining the role of private information and investor overconfidence.

Furthermore, this study complements the findings of Drake et al. (2015) by analyzing the consequences of increased investor attention for market efficiency. It examines how the generation of private information affects the efficiency of information transfers and the presence of over- and underreactions, addressing a gap in their research. By addressing these previously unanswered questions, this study contributes to a more nuanced understanding of investor behavior and information dynamics in sequential earnings announcements. It provides a theoretical framework for explaining seemingly contradictory market reactions and offers insights into the role of private information and overconfidence in shaping these dynamics.

The findings of this study also carry practical implications for investors, firms, and regulators. Specifically, investors should be mindful of the potential for overconfidence and biased information processing when reacting to peer earnings announcements. They should diligently evaluate both public and private information signals, avoiding an overreliance on private information or anecdotal evidence. Firms should recognize that their earnings announcements can trigger significant private information production among investors in peer firms. Therefore, clear and comprehensive disclosures are essential to minimize

information asymmetry and facilitate the accurate interpretation of earnings news. Investor relations efforts can also play a crucial role in managing investor expectations and promoting a balanced understanding of the firm's performance in relation to its industry peers. Policymakers can leverage these findings to enhance market transparency and efficiency. Regulations promoting the timely and comprehensive disclosure of information can help reduce information asymmetry and mitigate the risks associated with an overreliance on private information. Furthermore, investor education initiatives can raise awareness of behavioral biases and encourage sound investment practices.

2. Literature Review and Hypotheses Development

2.1. Peers' Earnings Announcements and Private Information Production

A long line of research on intra-industry information transfers argues that due to the economic relatedness among firms in the same industry, earnings announcements of one firm contain a common component that is also relevant to other firms in the industry. As a result, the earnings news of early-announcing peers is an important source of public information for investors to update their expectations about non-announcing firms (e.g., Hann et al., 2019; Liu et al., 2022). However, prior research on investors' information production suggests that information transfers may not necessarily involve public information only. Earnings announcements may stimulate more private information production, which can complement public earnings reports and enable market participants to produce unique insights to better identify profitable trading opportunities (e.g., Barron et al., 2002; Barron et al., 2005; Dyer, 2021; Crane et al., 2023). In this context, "private information" refers to insights and knowledge that are not publicly available or readily discernible from public sources. Examples include information obtained through proprietary research, channel checks, industry contacts, or the detailed analysis of complex financial data. This private information can provide investors with an informational advantage, allowing them to make more informed trading decisions. Based on this reasoning, I formulate the following hypothesis:

H1. Investors of the late-announcing firms produce more private information when earlyannouncing industry peers report earnings.

It is worth noting that this hypothesis posits a general relationship between peer earnings announcements and private information production about the late-announcing firm. It suggests that, on average, the amount of private information produced by investors in response to peer earnings news is greater than it would be in the absence of such news. This expectation is grounded in the idea that peer earnings announcements provide valuable information about industry trends, competitive dynamics, and the overall economic environment, which can stimulate investors to engage in more in-depth research and analysis to understand the implications for late-announcing firms.

While the magnitude of this effect may vary across firms with different characteristics (e.g., market conditions, firm size, analyst coverage, industry-specific factors), it is reasonable to expect that the general relationship will hold. This is because the underlying mechanism driving this relationship is rooted in the informational value of peer earnings announcements, which is relevant across a wide range of firms and industries.⁵

However, it is also possible that the above hypothesis may not hold. Prior research suggests that public information may substitute private information and that earnings announcements may actually decrease private information production (e.g., Gong et al., 2021; Stoumbos, 2023). Regulators such as the Securities and Exchange Commission (SEC) also view public disclosures such as earnings announcements as a mechanism that levels

the playing field and reduces the information advantage of a subset of informed investors (Securities and Exchange Commission, 2003). Thus, private information production about the late-announcing firms may not increase when industry peers announce earnings.

2.2. Overconfidence in Private Signals and the Efficiency of Information Transfers

Understanding the type (i.e., public versus private) of information that is involved in information transfers is important, as it has implications for the efficiency of investors' reactions to peers' earnings announcements. Specifically, a long line of research in behavioral finance suggests that people tend to overestimate (underestimate) the precision of private (public) information, since people in general are overconfident about their own abilities (e.g., Daniel et al., 1998). If investors produce more private information about the late-announcing firms when peers announce earnings, they may overweight private information and underweight the early announcers' public earnings reports when updating their expectations about the late-announcing firms. As a result, the late-announcing firms' own announcement excess returns may be negatively correlated with their returns on the early announcers' announcement days (i.e., an overreaction), while being positively related to the early announcers' own announcement excess returns (i.e., an underreaction) (Thomas & Zhang, 2008; Ramnath, 2002). Several characteristics of the overreaction documented in Thomas and Zhang (2008) are consistent with this overconfidence explanation. For example, they find that the overreaction is weaker on the first early announcer's announcement day and becomes stronger as subsequent early announcers report earnings. In addition, the overreaction is stronger when late-announcing firms' reactions to the early announcers' announcements are of the same sign. These are consistent with the evidence in prior research that overconfidence in private information builds up over time and is stronger when people's private signals are confirmed later on (e.g., Daniel et al., 1998).

In addition to accommodating the findings in Thomas and Zhang (2008), the theory of overconfidence can also generate new predictions about the mispricing in information transfers. Specifically, I expect both the over- and underreactions to be stronger when late-announcing firm investors are more likely to produce private information when the early-announcing peers announce earnings. This is because greater efforts in producing private information may not only magnify investors' overconfidence in their private signals, but also lower the weight they place on public signals. Therefore, I make the following hypotheses:

H2. Both the over- and underreactions are stronger when there is a higher level of private information production by late-announcing firm investors on the early-announcing firms' earnings announcement days.

3. Sample and Research Design

3.1. Sample

I started with all firm-quarters from the Compustat-CRSP merged database with non-missing earnings announcement dates, total assets, and sales, provided that the firms' shares are common stocks (share code 10 or 11). I then compared the earnings announcement dates from Compustat with those from the Institutional Brokers' Estimate System (I/B/E/S) and if the former did not concur with the latter, earnings announcement dates from I/B/E/S were used (e.g., Hand et al., 2021; Gallo et al., 2021). To ensure that my sample was compatible with those used in previous research (e.g., Thomas & Zhang, 2008), I focused on firms with December fiscal-year-ends and identified peers based on four-digit Standard Industrial Classification (SIC) industries. The selection of firms with a December fiscal year-end is justified for several reasons. First, this practice is overwhelmingly

common among US publicly listed companies in Compustat, with 74.3% adhering to this standard. This ensures the sample was representative of the broader market and minimizes potential selection bias. Second, using a uniform fiscal year-end is crucial for accurately capturing intra-industry information transfers. When firms have different fiscal year-ends, their earnings announcements pertain to different periods, introducing noise and potentially obscuring the information flow. Focusing on December year-end firms ensures that earnings information is contemporaneous, facilitating a cleaner and more precise analysis of information transfers within industries.

Following prior research, I required that the early announcers' announcement dates preceded non-announcing firms' announcement dates by at least five calendar days to mitigate the concern of very short-term price reversals (e.g., Jegadeesh et al., 2023). Due to the availability of the EDGAR Log File Data Sets, the sample period was 2003–2021. I collected accounting variables from Compustat, stock return data from Center for Research in Security Prices (CRSP), and analyst variables from I/B/E/S.

3.2. Research Design

3.2.1. Peers' Earnings Announcements and Private Information Production

To assess the extent of private information production by investors in late-announcing firms, I employed two complementary sets of measures. The first set was based on analysts' earnings forecasts, specifically the proportion of common information in analysts' forecasts (CONSENSUS) and the precision of their private information (PRECISION). The second set was based on investors' trading activities, specifically the probability of informed trading (PIN).

Following Barron et al. (2002), the proportion of common information to total information (CONSENSUS) in the analysts' forecasts issued over a particular period was calculated as 1 - D/V, where D is the sample variance of individual forecasts around the mean forecast, and V is the mean of the squared differences between individual forecasts and the realized earnings. The precision of analysts' private information (PRECISION) was calculated as (1 - CONSENSUS) * (1/V). These measures were chosen based on the premise that analysts' forecasts reflect, at least in part, the private information held by investors. This premise is supported by prior research, which shows that analysts often have access to and incorporate private information into their forecasts (e.g., Hossain et al., 2019; Balakrishnan et al., 2021). Therefore, changes in CONSENSUS and PRECISION of the late announcer after early-announcing industry peers' earnings announcements can be indicative of changes in the level of private information production by investors.

However, it is important to acknowledge that analysts' forecasts may not perfectly capture all private information held by investors. Some investors may possess unique insights or conduct independent research that is not reflected in analysts' forecasts. Additionally, analysts' forecasts can be influenced by factors other than private information, such as their relationships with management or their desire to maintain access to future information (e.g., Brown et al., 2022).

To complement the analysts' forecast-based measures and address their limitations, I also employed PIN, which was estimated following the approach described in Easley et al. (2002). PIN captures the probability of informed trading activity by investors of the late announcer, and provides a market-based perspective on their private information production that is distinct from the analyst-based perspective offered by CONSENSUS and PRECISION. It captures the extent to which private information is being actively used by investors to make trading decisions. However, PIN also has limitations. It may not capture all forms of private information, particularly information that is not actively traded upon. Additionally, PIN can be influenced by other factors unrelated to private information, such as liquidity or market volatility (e.g., Hung & Lai, 2022). By using both analysts' forecast-based measures and PIN, this study aims to provide a more balanced assessment of private information production. The limitations of one set of measures are mitigated by the strengths of the other, allowing for a more robust analysis of how peer earnings announcements affect private information generation in the equity market.

To gauge how industry peers' earnings announcements affect private information production regarding the late announcer using the analyst-based measures, I calculated the change in CONSENSUS and PRECISION regarding the late announcer after its industry peers started to announce earnings for the quarter. Specifically, for each firm-quarter, I identified the date when the first industry peer announced earnings. I then defined the period between the firm's earnings announcement date in the previous quarter and the first industry peer's announcement date in the current quarter as the pre-period, and the period between the first industry peer's announcement date and the firm's own announcement date in the current quarter as the post-period. Using analysts' forecasts for the firm's current quarter earnings issued in the pre- versus post-period, I calculated CONSENSUS and PRECISION before and after industry peers began to announce earnings. To test H1, I estimated the following regression:

$CONSENSUS_{i,q} \text{ (or PRECISION}_{i,q}) = \beta_0 + \beta_1 * POST_{i,q} + Controls + Firm FE + Year-quarter FE,$ (1)

where $\text{POST}_{i,q}$ is an indicator variable equal to one if CONSENSUS (or PRECISION) is measured using forecasts issued in the post-period, and zero otherwise. If H1 holds, β_1 is predicted to be significantly negative (positive) when CONSENSUS (PRECISION) is the dependent variable. The following variables were included as controls: (1) The average length of time between the announcement date of the forecasts and firm i's earnings announcement date in current quarter q (LOG_NDAYS). This controls for the possibility that forecasts issued closer to the earnings announcement date may be more informed. (2) Firm i's analyst coverage (LOGACOV), which controls for the influence of analyst attention on forecast properties. (3) Return-on-assets (ROA). This controls for the firm's underlying profitability, which can influence both analyst forecasts and investor information production as higher profitability may attract more attention from analysts and investors, leading to more accurate forecasts and potentially more private information production. (4) Firm size (LOGSIZE), which controls for the effect of firm size on information production. Larger firms may be subject to more scrutiny and attract more investor attention, potentially leading to more private information production. (5) Book-to-market ratio (LOGBM). This controls for the firm's growth opportunities and risk profile, which can influence investor behavior and information production. (6) Institutional ownership (INSTOWN), which controls for the influence of institutional investors on information production, as they may have greater resources and incentives to acquire private information. All the control variables were measured as of the end of the previous fiscal year.⁶

As this analysis focused on comparing the properties of analyst forecasts in the presence of peer earnings announcements to those in the absence of such announcements, firm fixed effects were included in the regression to control for time-invariant firm characteristics that may affect analyst forecasts. The firm fixed effects can also indirectly control for industry-level factors that may affect the dependent variables, since the fixed effect for each firm will absorb the average effect of being in a particular industry. The year-quarter fixed effects aimed to capture the unique effect of each individual quarter within each year. They account for any factors that vary both across quarters and across years, including seasonality (i.e., recurring patterns within each year), year-specific shocks (i.e., events or trends that impact a particular year as a whole), and their combined effects. Therefore, these two sets of fixed effects address the concern that industry-specific or seasonal factors could skew the results. Standard errors were double-clustered by firm and quarter (Petersen, 2009) to account for potential correlation within both dimensions.

To examine the effects of peer earnings announcements on private information production using PIN, I used the following procedures. For each firm-year, I identified days when early-announcing industry peers reported earnings (i.e., announcement days) and days when there were no peer earnings announcements (i.e., no-announcement days). I excluded days when firm i announced its own earnings or earnings guidance from the analysis as prior research shows that own-firm disclosures stimulate private information production (e.g., Gao & Huang, 2020). I then estimated PIN separately for a particular firm-year using the daily number of buy and sell trades on announcement (PIN_AD) versus noannouncement days (PIN_NAD). Following Easley et al. (2002), at least sixty non-missing observations are required to estimate PIN.⁷ I then estimated the following regression:

$$PIN_{i,q} = \beta_0 + \beta_1 * AD_{i,q} + Controls + Firm FE + Year FE,$$
(2)

where $AD_{i,q}$ is an indicator variable equal to one if PIN is estimated using the days when early-announcing industry peers report earnings, and zero otherwise. Under H1, β_1 is expected to be significantly positive. The other specifications of regression (2) were the same as in regression (1).

3.2.2. Peer-Triggered Private Information Production and the Efficiency of Information Transfers

To test H2, I estimated the following regression:

 $RET_LO_{i,q} = \beta_0 + \beta_1 * RET_LE_{i,d,q} + \beta_2 * RET_EO_{i,d,q} + \beta_3 * COND_{i,q} + \beta_4 * RET_LE_{i,d,q} * COND_{i,q} + \beta_5 * RET_EO_{i,d,q} * COND_{i,q} + Controls + Industry FE + Year-quarter FE,$ (3)

where RET_LO_{i,q} is the one-day market-adjusted excess return of late-announcing firm i on its own earnings announcement day in quarter q (i.e., firm i's reaction to its own earnings announcement). RET_LE_{i.d.g} is the one-day market-adjusted excess return of firm i on early announcers' announcement day d in quarter q (i.e., firm i's reaction to early announcers' earnings announcements on a particular day d). RET_EO_{i.d.g} is the average of the one-day market-adjusted excess returns of all early announcers that report earnings on day d in quarter q (i.e., the average of the early announcers' reactions to their own earnings announcements). I used one-day excess returns in the main analysis to provide a cleaner measure of market reactions to early announcers' announcements, since earnings announcements tend to cluster for firms in the same industry. COND takes the value of one of the following three variables: RANK_D_CONSENSUS, RANK_D_PRECISION, and RANK_D_PIN. RANK_D_CONSENSUS (RANK_D_PRECISION) is the quartile ranking of the change in the late announcer's CONSENSUS (PRECISION) in the post-period, calculated as the difference between CONSENSUS (PRECISION) estimated over the postperiod and the pre-period. RANK_D_PIN is the quartile ranking of the change in the late announcer's PIN when early-announcing peers report earnings, calculated as its PIN over the peer announcement days and no-announcement days. If H2 holds, I expected β_4 to be significantly positive (negative) and β_5 to be significantly negative (positive) when the conditioning variable is RANK_D_CONSENSUS (RANK_D_PRECISION or RANK D PIN) in regression (3).

Consistent with prior research (e.g., Thomas & Zhang, 2008), I included the following as control variables: the logarithm of firm i's market capitalization (LOGSIZE), the logarithm of firm i's book-to-market ratio (LOGBM), and firm i's total accruals (ACC), all measured as of the end of the previous quarter. I also included firm i's one-day excess returns around its own announcement in q-1 (LAG1Q_RETLO) and q-4 (LAG4Q_RETLO), as well as its buy-and-hold six-month returns up to one week before its earnings announcement in current quarter q (RET6).⁸ Industry fixed effects were included in the regression as they offer an effective control for common, industry-level shocks that affect firm returns without over-controlling for the relevant variation of interest.⁹ The year-quarter fixed effects controlled for the effects of seasonal and year-specific factors that may affect stock returns. Standard errors were double-clustered by firm and quarter.

4. Main Results

4.1. Peers' Earnings Announcements and Private Information Production

4.1.1. Descriptive Statistics

Table 1 presents descriptive statistics for the main sample. In Panel A, the variables were measured for each firm-quarter. The mean (median) of PRE_CONSENSUS was 0.516 (0.649) and the standard deviation was 0.439. The mean (median) of POST_CONSENSS was 0.422 (0.466) and the standard deviation was 0.512. PRE_PRECISION had a mean (median) of 2404.472 (109.332) and a standard deviation of 5388.65. POST_PRECISION had a mean (median) of 3004.380 (219.850) and a standard deviation of 7670.15.¹⁰ In Panel B, the variables were measured for each firm-year. PIN_AD had a mean (median) of 0.249 (0.250) and a standard deviation of 0.094. PIN_NAD had a mean (median) of 0.249 (0.250) and a standard deviation of 0.092. These statistics are compatible with the results reported in Easley et al. (2002).

4.1.2. Results

Table 2, Panel A presents the estimation results for regression (1) using ordinary least squares (OLS) regressions.¹¹ In column (1), where the dependent variable is CONSENSUS, the coefficient on POST was significantly negative at the 1% level, suggesting that CON-SENSUS is lower when analysts' forecasts are issued after the first industry peer's earnings announcements. The coefficient on LOG_NDAYS was significantly positive, indicating that analysts produce more private information as the late announcer's own earnings announcement date becomes closer. The coefficient on ROA was significantly negative, while that on LOGBM was significantly positive, implying that analysts are more incentivized to seek private information when the firm is more profitable or has more growth opportunities. In column (2), where the dependent variable is PRECISION, POST was significantly positive at the 1% level, implying that PRECISION is higher when analysts' forecasts are issued in the post-period. The signs of the coefficients on the control variables corroborate those in column (1). Panel B reports the results of quantile regressions, which address potential bias in the OLS estimates due to the non-normal distribution of CONSENSUS and PRECISION. The inferences derived from the quantile regressions were qualitatively similar to those from the OLS regressions, supporting the robustness of the findings. Thus, the results using analyst-based measures of private information production support the hypothesis that late announcer investors are incentivized to produce more private information when peers announce earnings.

Table 3, Panel A reports the estimation results for regression (2) using OLS regression.¹² The coefficient on the AD indicator was significantly positive at the 1% level, suggesting that the PIN is higher on days when early-announcing peers report earnings than on days when no peers announce earnings. The coefficients on LOGACOV and LOGSIZE were significantly negative, indicating that investors are less likely to trade on private information for large firms and firms with higher analyst coverage. The coefficient on ROA was significant at the 10% level, suggesting that investors are more likely to engage in private information production for more profitable firms. To address potential bias from

the non-normal distribution of the PIN, Panel B presents quantile regression results, which qualitatively confirm the OLS findings. Taken together, the evidence in Tables 2 and 3 is consistent with peers' earnings announcements stimulating private information production by late announcer investors.

Panel A. OLS Regressions		
Dependent variable:	CONSENSUS	PRECISION
	(1)	(2)
POST	-0.086 ***	604.370 ***
	(-3.167)	(12.341)
LOG_NDAYS	0.310 ***	-2056.360 ***
	(13.732)	(-21.870)
LOGACOV	-0.016	122.870
	(-1.518)	(0.635)
ROA	-0.063 *	8726.740 ***
	(-1.820)	(9.363)
LOGSIZE	0.036	-655.710
	(1.272)	(-1.077)
LOGBM	0.013 *	-1129.590 ***
	(1.895)	(-6.709)
INSTOWN	0.130	-838.970
	(0.451)	(-1.145)
Firm Fixed Effects	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes
Observations	106,850	106,850
Adjusted R-squared	0.085	0.023
Panel B. Quantile Regressions		
~ 0		
Dependent variable:	CONSENSUS	PRECISION
Dependent variable:	CONSENSUS (1)	PRECISION (2)
Dependent variable:	CONSENSUS (1) -0.117 ***	PRECISION (2) 107.405 ***
Dependent variable: POST	CONSENSUS (1) -0.117 *** (-3.492)	PRECISION (2) 107.405 *** (13.782)
Dependent variable: POST LOG_NDAYS	CONSENSUS (1) -0.117 *** (-3.492) 0.113 ***	PRECISION (2) 107.405 *** (13.782) -61.718 ***
Dependent variable: POST LOG_NDAYS	(1) -0.117 *** (-3.492) 0.113 *** (6.079)	PRECISION (2) 107.405 *** (13.782) -61.718 *** (-8.877)
Dependent variable: POST LOG_NDAYS LOGACOV	(1) -0.117 *** (-3.492) 0.113 *** (6.079) -0.069	PRECISION (2) 107.405 *** (13.782) -61.718 *** (-8.877) 34.716
Dependent variable: POST LOG_NDAYS LOGACOV	CONSENSUS (1) -0.117 *** (-3.492) 0.113 *** (6.079) -0.069 (-0.944)	PRECISION (2) 107.405 *** (13.782) -61.718 *** (-8.877) 34.716 (0.726)
Dependent variable: POST LOG_NDAYS LOGACOV ROA	CONSENSUS (1) -0.117 *** (-3.492) 0.113 *** (6.079) -0.069 (-0.944) -0.220 ***	PRECISION (2) 107.405 *** (13.782) -61.718 *** (-8.877) 34.716 (0.726) 301.127 ***
Dependent variable: POST LOG_NDAYS LOGACOV ROA	CONSENSUS (1) -0.117 *** (-3.492) 0.113 *** (6.079) -0.069 (-0.944) -0.220 *** (-3.295)	PRECISION (2) 107.405 *** (13.782) -61.718 *** (-8.877) 34.716 (0.726) 301.127 *** (13.506)
Dependent variable: POST LOG_NDAYS LOGACOV ROA LOGSIZE	(1) -0.117 *** (-3.492) 0.113 *** (6.079) -0.069 (-0.944) -0.220 *** (-3.295) -0.001	PRECISION (2) 107.405 *** (13.782) -61.718 *** (-8.877) 34.716 (0.726) 301.127 *** (13.506) -12.431
Dependent variable: POST LOG_NDAYS LOGACOV ROA LOGSIZE	(1) -0.117 *** (-3.492) 0.113 *** (6.079) -0.069 (-0.944) -0.220 *** (-3.295) -0.001 (-0.847)	PRECISION (2) 107.405 *** (13.782) -61.718 *** (-8.877) 34.716 (0.726) 301.127 *** (13.506) -12.431 (-1.403)
Dependent variable: POST LOG_NDAYS LOGACOV ROA LOGSIZE LOGBM	$\begin{array}{c} \text{CONSENSUS} \\ (1) \\ -0.117 *** \\ (-3.492) \\ 0.113 *** \\ (6.079) \\ -0.069 \\ (-0.944) \\ -0.220 *** \\ (-3.295) \\ -0.001 \\ (-0.847) \\ 0.005 * \end{array}$	PRECISION (2) 107.405 *** (13.782) -61.718 *** (-8.877) 34.716 (0.726) 301.127 *** (13.506) -12.431 (-1.403) -56.830 ***
Dependent variable: POST LOG_NDAYS LOGACOV ROA LOGSIZE LOGBM	$\begin{array}{c} \text{CONSENSUS} \\ (1) \\ -0.117 *** \\ (-3.492) \\ 0.113 *** \\ (6.079) \\ -0.069 \\ (-0.944) \\ -0.220 *** \\ (-3.295) \\ -0.001 \\ (-0.847) \\ 0.005 * \\ (1.909) \end{array}$	PRECISION (2) 107.405 *** (13.782) -61.718 *** (-8.877) 34.716 (0.726) 301.127 *** (13.506) -12.431 (-1.403) -56.830 *** (-7.329)
Dependent variable: POST LOG_NDAYS LOGACOV ROA LOGSIZE LOGBM INSTOWN	CONSENSUS (1) -0.117 *** (-3.492) 0.113 *** (6.079) -0.069 (-0.944) -0.220 *** (-3.295) -0.001 (-0.847) 0.005 * (1.909) 0.065	$\begin{array}{r} \hline \\ (2) \\ 107.405 *** \\ (13.782) \\ -61.718 *** \\ (-8.877) \\ 34.716 \\ (0.726) \\ 301.127 *** \\ (13.506) \\ -12.431 \\ (-1.403) \\ -56.830 *** \\ (-7.329) \\ -49.529 \end{array}$
Dependent variable: POST LOG_NDAYS LOGACOV ROA LOGSIZE LOGBM INSTOWN	$\begin{array}{c} \text{CONSENSUS} \\ (1) \\ -0.117 *** \\ (-3.492) \\ 0.113 *** \\ (6.079) \\ -0.069 \\ (-0.944) \\ -0.220 *** \\ (-3.295) \\ -0.001 \\ (-0.847) \\ 0.005 * \\ (1.909) \\ 0.065 \\ (1.176) \end{array}$	$\begin{array}{r} \label{eq:precision} \\ (2) \\ 107.405 *** \\ (13.782) \\ -61.718 *** \\ (-8.877) \\ 34.716 \\ (0.726) \\ 301.127 *** \\ (13.506) \\ -12.431 \\ (-1.403) \\ -56.830 *** \\ (-7.329) \\ -49.529 \\ (-0.718) \end{array}$
Dependent variable: POST LOG_NDAYS LOGACOV ROA LOGSIZE LOGBM INSTOWN Firm Fixed Effects	$\begin{array}{c} \text{CONSENSUS} \\ (1) \\ -0.117 *** \\ (-3.492) \\ 0.113 *** \\ (6.079) \\ -0.069 \\ (-0.944) \\ -0.220 *** \\ (-3.295) \\ -0.001 \\ (-0.847) \\ 0.005 * \\ (1.909) \\ 0.065 \\ (1.176) \\ \text{Yes} \end{array}$	$\begin{array}{r} \label{eq:precision} \\ (2) \\ 107.405 *** \\ (13.782) \\ -61.718 *** \\ (-8.877) \\ 34.716 \\ (0.726) \\ 301.127 *** \\ (13.506) \\ -12.431 \\ (-1.403) \\ -56.830 *** \\ (-7.329) \\ -49.529 \\ (-0.718) \\ Yes \end{array}$
Dependent variable: POST LOG_NDAYS LOGACOV ROA LOGSIZE LOGBM INSTOWN Firm Fixed Effects Year-quarter Fixed Effects	$\begin{array}{c} \text{CONSENSUS} \\ (1) \\ -0.117 *** \\ (-3.492) \\ 0.113 *** \\ (6.079) \\ -0.069 \\ (-0.944) \\ -0.220 *** \\ (-3.295) \\ -0.001 \\ (-0.847) \\ 0.005 * \\ (1.909) \\ 0.065 \\ (1.176) \\ \text{Yes} \\ \text{Yes} \\ \text{Yes} \end{array}$	(2) 107.405 *** (13.782) -61.718 *** (-8.877) 34.716 (0.726) 301.127 *** (13.506) -12.431 (-1.403) -56.830 *** (-7.329) -49.529 (-0.718) Yes Yes
Dependent variable: POST LOG_NDAYS LOGACOV ROA LOGSIZE LOGBM INSTOWN Firm Fixed Effects Year-quarter Fixed Effects Observations	$\begin{array}{c} \text{CONSENSUS} \\ (1) \\ -0.117 *** \\ (-3.492) \\ 0.113 *** \\ (6.079) \\ -0.069 \\ (-0.944) \\ -0.220 *** \\ (-3.295) \\ -0.001 \\ (-0.847) \\ 0.005 * \\ (1.909) \\ 0.065 \\ (1.176) \\ \text{Yes} \\ \text{Yes} \\ \text{Yes} \\ 106,850 \end{array}$	$\begin{array}{r} \hline \\ (2) \\ 107.405 *** \\ (13.782) \\ -61.718 *** \\ (-8.877) \\ 34.716 \\ (0.726) \\ 301.127 *** \\ (13.506) \\ -12.431 \\ (-1.403) \\ -56.830 *** \\ (-7.329) \\ -49.529 \\ (-0.718) \\ Yes \\ Yes \\ Yes \\ 106,850 \\ \end{array}$

Table 2. Peer earnings announcements and analysts' private information production.

Table 2 reports the estimation results of whether early-announcing peers' earnings announcements stimulate analysts' private information production for the late-announcing firms. Panel A presents the estimation results using OLS regressions. The t-statistics (presented in parentheses) are based on standard errors double-clustered by firm and quarter. Panel B presents the estimation results using quantile regressions. * and *** represent significance at the 10% and 1% level, respectively. All variables are defined in Appendix B.

Panel A. OLS Regression	
Dependent variable:	PIN
AD	0.008 ***
	(2.883)
LOGACOV	-0.010 ***
	(-5.698)
ROA	0.002 *
	(1.933)
LOGSIZE	-0.017 ***
	(-7.736)
LOGBM	0.002
	(1.580)
INSTOWN	0.026 ***
	(5.395)
Firm Fixed Effects	Yes
Year Fixed Effects	Yes
Observations	20,860
Adjusted R-squared	0.176
Panel B. Quantile Regression	
Dependent variable:	PIN
AD	0.028 ***
	(6.710)
LOGACOV	-0.013 ***
	(-9.226)
ROA	0.001
	(1.562)
LOGSIZE	-0.016 ***
	(-6.069)
LOGBM	0.001
	(0.941)
INSTOWN	0.016 ***
	(3.636)
Firm Fixed Effects	Yes
Year Fixed Effects	Yes
Observations	20,860
Adjusted R-squared	0.174

Table 3. Peer earnings announcements and probability of informed trading.

Table 3 reports the estimation results of whether early announcing peers' earnings announcements are associated with higher PIN for the late-announcing firms. The regression was estimated using pooled observations of PIN_AD and PIN_NAD. Panel A presents the estimation results using OLS regression. The t-statistics (presented in parentheses) are based on standard errors double-clustered by firm and quarter. Panel B presents the estimation results using quantile regression. * and *** represent significance at the 10% and 1% level, respectively. All variables are defined in Appendix B.

4.2. Peer-Triggered Private Information Production and the Efficiency of Information Transfers

Before discussing the estimation results for H2, I first replicated the findings in previous studies to check whether the over- and underreactions in information transfers still existed in the present sample. Table 4, Panel A provides the descriptive statistics for the main return variables, and the distributions of RET_LO, RET_LE, and RET_EO were similar to those reported in Thomas and Zhang (2008). Panel B presents the estimation results of an OLS model, which regresses RET_LO on RET_LE, RET_EO, and control variables following the specification in Thomas and Zhang (2008) in column (1) and with industry and year-quarter fixed effects in column (2).¹³ The significantly negative (positive) coefficient on RET_LE (RET_EO) indicated that the overreaction (underreaction) anomaly still exists in the more recent periods examined in this study.

Panel A. Descriptive Statistics				
	RET_LO		RET_LE	RET_EO
Mean	0.000		0.000	0.000
Std.	0.041		0.028	0.031
P75	0.018		0.012	0.011
Median	0.000		-0.001	0.000
P25	-0.017		-0.013	-0.012
Ν	961,206		961,206	961,206
Panel B. Replication	of Over- and	Underreactions	in Information	n Transfers
Dependent variabl	e:		RET_LO	
		(1)		(2)
RET_LE		-0.011 ***		-0.09 ***
		(-4.434)		(-2.619)
RET_EO		0.008 ***		0.007 ***
		(4.568)		(3.496)
LOGSIZE		0.000		0.000
		(0.421)		(0.560)
LOGBM		0.001 ***		0.002 **
		(4.410)		(2.039)
ACC		-0.002 *		-0.001
		(-1.803)		(-1.014)
LAG1Q_RETLO		0.007 ***		0.006 **
		(2.752)		(2.157)
LAG4Q_RETLO		0.005 *		0.003
		(1.778)		(1.294)
RET6		0.000		0.000
		(0.047)		(0.018)
Industry FE		No		Yes
Year-quarter FE		No		Yes
Observations		961,206		961,206
Adjusted R-square	ed	0.001		0.036

Table 4. Replication of over- and underreactions in information transfers.

Table 4 reports the estimation results on whether the over- and underreactions in information transfers documented in previous studies still exist in the sample used in this study. Panel A provides descriptive statistics for the main return variables. Panel B presents estimation results of regression analysis. The t-statistics (presented in parentheses) are based on standard errors double-clustered by firm and quarter. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. All variables are defined in Appendix B.

Table 5 presents the estimation results for H2 using OLS regression models.¹⁴ Panel A tabulates the findings when the conditioning variables are the analyst-based private information production measures. In column (1), the coefficient on RET_LE was significantly negative while the coefficient on RET_EO was significantly positive, indicating the presence of over- and underreaction in the bottom quartile of D_CONSENSUS. The coefficient on the interaction between RET_LE (RET_EO) and RANK_D_CONSENSUS was significantly positive (negative), suggesting that the over- and underreaction become weaker for firms with a higher value of D_CONSENSUS. In column (2), the coefficients on RET_LE and RET_EO were both statistically insignificant, while the coefficient on the interaction between RET_LE (RET_EO) and RANK_D_PRECISION was significantly negative (positive). This implies that both the over- and underreaction are stronger when the firm experiences a greater increase in the precision of analysts' private information. Similar observation can be made in Panel B where the conditioning variable is RANK_D_PIN. Specifically, while there is little evidence of over- and underreaction in the lowest quartile of D_PIN, the extent of over- and underreaction becomes stronger when the firm has a greater increase in the PIN on the peers' earnings announcement days, as indicated by the significantly negative

(positive) coefficient on the interaction between RET_LE (RET_EO) and RANK_D_PIN. Overall, the evidence in Table 5 is consistent with the prediction in H2 that mispricing is more pronounced when late announcer investors produce more private information when the early announcers report earnings.

Panel A. Analyst-Based Measures			
Dependent variable:		RET_LO	
RET_LE	(1) -0.016 ** (-2.252)		(2) -0.003 (-1.356)
RET_EO	0.010 *** (2.951)		0.002
RANK_D_CONSENSUS	0.001 (1.254)		()
RET_LE*RANK_D_CONSENSUS	0.003 ** (2.344)		
RET_EO*RANK_D_CONSENSUS	-0.002 ** (-2.096)		
RANK_D_PRECISION	~ /		0.000 (0.693)
RET_LE*RANK_D_PRECISION			-0.004 *** (-2.944)
RET_EO*RANK_D_PRECISION			0.003 ** (2.174)
LOGSIZE	0.000 (0.592)		0.001 (1.524)
LOGBM	0.001 **		0.001 *** (2.723)
ACC	(-1.029)		(-0.005) (-0.952)
LAG1Q_RETLO	0.003		0.007
LAG4Q_RETLO	(0.011) 0.005 (0.335)		0.012 *
RET6	0.001 (0.538)		0.001 (0.691)
Industry FE	Yes		Yes
Year-quarter FE	Yes		Yes
Observations	961,206		961,206
Adjusted R-squared	0.036		0.036
Panel B. Investor-Based Measure			
Dependent variable:		RET_LO	
RET_LE		-0.002 (1.07)	
RET_EO		0.002 (1.352)	
RANK_D_PIN		0.000	
RET_LE*RANK_D_PIN		-0.003 *** (3.113)	
		(0.110)	

Table 5. Are over- and underreactions stronger when private information production is higher?

Panel B. Investor-Based Measure		
RET_EO*RANK_D_PIN	0.002 **	
	(2.379)	
LOGSIZE	0.000	
	(0.317)	
LOGBM	0.002 ***	
	(3.006)	
ACC	-0.002	
	(-1.423)	
LAG1Q_RETLO	0.007 **	
	(2.050)	
LAG4Q_RETLO	0.003	
	(0.684)	
RET6	0.000	
	(0.723)	
Industry FE	Yes	
Year-quarter FE	Yes	
Observations	961,206	
Adjusted R-squared	0.036	

Table 5. Cont.

Table 5 reports the estimation results on whether over- and underreactions are stronger when late-announcing firm investors engage in more private information production. Panel A (Panel B) tabulates the results using analyst-based (investor-based) private information production measures. The t-statistics (presented in parentheses) are based on standard errors double-clustered by firm and quarter. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. All variables are defined in Appendix B.

5. Additional Analysis and Robustness Checks

5.1. Cross-Sectional Analysis

To provide further evidence that the over- and underreactions in information transfers can be attributed to investors' private information production, I considered two scenarios where early announcers' earnings reports are more likely to encourage private information production by late-announcing firms' investors. The first is when the peer's earnings announcements are more relevant to the late announcer, since the earnings news from a more relevant peer can enhance the value of private information, thereby enabling investors to develop a more precise signal about the late announcer's prospects (e.g., Dyer, 2021; Crane et al., 2023). I used two methods to identify the earnings announcements of relevant peers. First, I used the pairwise product similarity score developed in Hoberg and Phillips (2010, 2016) to identify close peers to the late announcer. Specifically, I designated the top quarter (or third) of a late-announcing firm's TNIC3 peers (in terms of similarity scores) as of the end of the previous year as close peers. I then defined an indicator variable (CLOSEPEER) that is equal to one if at least one early announcer on a certain day is a close peer to a particular late-announcing firm, and 0 otherwise.

Second, I leveraged the detailed records of search traffic for firms on the EDGAR website to infer the relevance of a peer's earnings from the amount of investor attention to the late announcer when an early announcer reports earnings. Drake et al. (2015) showed that EDGAR searches related to a firm increase significantly when industry peers announce earnings and interpreted this finding as evidence that peers' earnings announcements increase the level of investor attention for non-announcing firms. To the extent that the earnings announcement from a more relevant peer elicits more attention from late announcer investors, and that attention is positively correlated with efforts to produce private information about the firm (e.g., Schneemeier, 2023), abnormal EDGAR search traffic on the early announcers' announcement days can be used to proxy for the amount of private information produced by late announcer investors.

I measured EDGAR search traffic as the number of daily EDGAR searches for a particular firm. Only searches related to non-index pages with a file size greater than zero and the file type being "htm" or "txt" were included in the analysis. The restriction on file type was imposed because firms' financial statements and other filings are generally in "htm" or "txt" formats on the EDGAR website. Abnormal EDGAR search traffic (D_EDGAR) was calculated as the difference between the number of EDGAR searches for a particular late announcer on an early-announcer's earnings announcement day (EDGAR_AD) and the average number of EDGAR searches for the late announcer on days without peer earnings announcements in the same quarter (EDGAR_NAD).¹⁵

Besides peer news relevance, I also examined if the over- and underreactions are stronger when the early announcers' news has ambiguous implications for the late-announcing firms. When some peers report positive news while others report negative news, it is more difficult to make a clear-cut prediction about the late-announcing firm's earnings. As a result, pre-announcement private information production is more profitable, as the late announcer's announcement can resolve more uncertainty (e.g., Bolandnazar et al., 2020). In addition, inferring late-announcing firms' earnings involves more judgment when early announcers have mixed news, making investors more prone to overconfidence bias (e.g., Daniel et al., 1998).¹⁶

I developed two measures to gauge the early-announcers' news ambiguity. The first is the negative of the absolute value of the difference between the percentage of positive and negative news of early announcers that report earnings on a particular day (MIX). MIX has a value of -1 when all early announcers' earnings news on a certain day has the same sign, and a value of zero when exactly half of the early announcers report positive news while the other half report negative news. The second is the dispersion of early announcers' news on a given day (DISP), where news is calculated as the early announcer's one-day market-adjusted returns over its own earnings announcement window. I then modified regression (3) by replacing the conditioning variable (COND) with CLOSEPEER, the quartile ranking of D_EDGAR (RANK_D_EDGAR), and the quartile rankings of MIX (RANK_MIX) and DISP (RANK_DISP).

The estimation results are tabulated in Table 6.¹⁷ Panel A reports the evidence from the peer news relevance tests. In column (1) and (2), the conditioning variable is CLOSEPEER, and the coefficient on the interaction variable between RET LE (RET EO) and CLOSEPEER was significantly negative (positive), suggesting that the over- and underreactions are both stronger when close peers announce earnings. In column (3), the conditioning variable is RANK_D_EDGAR. While the coefficients on RET_LE and RET_EO were statistically insignificant, the coefficient on the interaction between RET_LE and RANK_D_EDGAR was significantly negative, and the coefficient on the interaction between RET_EO and RANK_D_EDGAR was significantly positive. These findings suggest that the mispricing becomes more pronounced when more relevant peer announcements attract more investor attention to the late announcer.¹⁸ Panel B presents the results on whether the over- and underreactions are stronger when early announcers report mixed earnings news. In column (1), RANK_MIX was used to measure early announcers' news ambiguity and the coefficient on the interaction between RET_LE (RET_EO) and RANK_MIX was significantly negative (positive), both at the 10% level. Similar inferences can be made from column (2), where the conditioning variable is RANK_DISP. These findings are consistent with the prediction that the over- and underreactions are stronger when early announcers' news has ambiguous implications for the late-announcing firm. Collectively, the evidence from Table 6 lends further support for the conjecture that the mispricing in information transfers can be attributed to late announcer investors' private information production on the early announcers' earnings announcement days.

Dopondont variable:		PET IO	
	Class page (dafin	M hu ton TNIC2 norm	Abr EDCAR soorch troffic
reer news relevance measured by		True 1 (2	ADII. EDGAK search trainc
	10p 1/4	10p 1/3	(2)
	(1)	(2)	(3)
RET_LE	-0.006 * (-1.659)	-0.004 (-1.548)	-0.002 (-0.540)
RET_EO	0.006 ** (2.066)	0.005 * (1.746)	0.002 (0.612)
CLOSEPEER	0.000	0.000 (1.209)	
RET_LE*CLOSEPEER	-0.009 ** (-1.985)	-0.012 ** (-1.982)	
RET_EO*CLOSEPEER	0.007 *	0.008 **	
RANK_D_EDGAR	(1.920)	(1.900)	-0.001
RET_LE*RANK_D_EDGAR			(-0.728) -0.002 ** (-2.498)
RET_EO*RANK_D_EDGAR			(-2.293) 0.003 *** (2.826)
LOGSIZE	0.001	0.000	0.001
LOGBM	0.001 **	0.001 ***	0.001 **
ACC	(2.075) -0.003 (-0.955)	(2.777) -0.003 (-0.954)	(2.00) -0.005 (-1.375)
LAG1Q_RETLO	0.007 *	0.007 *	0.002
LAG4Q_RETLO	0.002	0.002	0.001 *
RET6	0.001	(0.011) (0.001) (0.692)	(-0.076)
Industry FE	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes
Observations	961,206	961,206	961,206
Adjusted R-squared	0.036	0.036	0.036
Panel B. Peer News Ambiguity			
Dependent variable:		RET_LO	
Peer news ambiguity measured by	MIX		DISP
	(1)		(2)
RET_LE	-0.006 * (-1.788)		-0.007 * (-1.721)
RET_EO	0.009 *** (3.029)		0.005 * (1.682)
RANK_MIX	0.00 (0.341)		× /
RET_LE*RANK_MIX	-0.003 * (-1 874)		
RET_EO*RANK_MIX	0.002 *		
RANK_DISP	(1.000)		0.000

Table 6. Cross-sectional analysis.

Panel B. Peer News Ambiguity		
Dependent variable:		RET_LO
Peer news ambiguity measured by	MIX	DISP
		(0.282)
RET_LE*RANK_DISP		-0.003 *
DET EO*DANIZ DICD		(-1.926)
KET_EO'KAINK_DISP		(2.066)
LOGSIZE	0.000	0.000
	(1.031)	(0.392)
LOGBM	0.001 ***	0.001 ***
	(2.791)	(2.749)
ACC	-0.003	-0.003
	(-0.951)	(-0.946)
LAG1Q_RETLO	0.007 ***	0.007 ***
	(2.767)	(2.723)
LAG4Q_RETLO	0.002	0.002
	(0.687)	(0.512)
RET6	0.000	0.001
	(0.787)	(1.024)
Industry FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	961,206	961,206
Adjusted R-squared	0.036	0.036

Table 6 reports the estimation results from cross-sectional analysis. Panel A tabulates the results on whether the over- and underreactions are stronger when the early announcers' earnings announcements are more relevant to the late announcer. Panel B presents the results on whether the mispricing is more pronounced when the early announcers' earnings announcements have ambiguous implications for late-announcing firms' earnings. The t-statistics (presented in parentheses) are based on standard errors double-clustered by firm and quarter. *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively. All variables are defined in Appendix B.

5.2. Robustness Checks

In this section, I discuss the results from several alternative specifications to ensure the robustness of the findings. First, I conducted a series of sensitivity analyses addressing potential alternative explanations for the observed over- and underreaction anomalies, including liquidity constraints, investor attention, and firm characteristics (e.g., size, industry competition). Liquidity constraints can impact a firm's ability to respond to new information, potentially causing a divergence between the firm's fundamental value and its market price (e.g., Schauer et al., 2019). Variations in investor attention can influence the speed and accuracy of information processing and thus the extent of mispricing (e.g., Blankespoor et al., 2020). Differences in firm characteristics, such as size and industry competition, can also affect the magnitude of over- and underreactions, as larger firms or those in more competitive industries may attract greater investor scrutiny, leading to more efficiency information processing and reduced anomalies (e.g., Blankespoor, 2019; Durnev & Mangen, 2020).

To examine whether private information production remains a robust explanatory factor for the over- and underreaction anomalies after controlling for these alternative explanations, I augmented the three tests in Table 5 by including interaction terms between the relevant variables (RET_LE, RET_EO) and proxies for liquidity constraints (RANK_LIQCONSTR), investor attention (RANK_LOGACOV), firm size (RANK_LOGSIZE), and industry competition (RANK_HHI).¹⁹ The estimation results (unt-

Table 6. Cont.

20 of 25

abulated) demonstrated that the interaction terms related to private information production retained their significance and direction after accounting for these alternative factors.

Second, to check whether the results were robust to other definitions of industry peers, I repeated all analyses reported in Tables 2–6 with peers defined using eight-digit GICS industries or the TNIC3 industries. The results (untabulated) were qualitatively similar when these alternative industry classification schemes were used.

Third, to ensure the robustness of the findings to alternative definitions of event windows, I used three-day [-1, +1] market-adjusted returns to examine the relationship between the mispricing and investors' private information production, and the results in Tables 4–6 remained qualitatively similar. These findings support the robustness of the main results and underscore the importance of private information production in explaining the over- and underreaction anomalies in intra-industry information transfers.

6. Conclusions

This study provides new insights into how investors respond to peer earnings announcements. Contrary to the common belief that investors primarily focus on public information in the information transfer process, this study finds that they actually generate more private information when peers in the same industry announce their earnings. This increase in private information production can lead to both over- and underreactions in stock prices due to investor overconfidence and biased information processing. The findings highlight the important role of private information in shaping investor behavior and market dynamics. They also offer a potential explanation for the seemingly contradictory presence of both over- and underreactions in stock prices following peer announcements. Future research could explore the specific types of private information that investors gather in response to peer announcements, as well as the factors that drive variations in private information production across different firms and industries. This research could further enhance our understanding of information efficiency and investor behavior in financial markets.

Funding: This research and its APC was funded by the Wenzhou-Kean University 2024 Internal Faculty/Staff Research Support Programs [Grant number: IRSPC2024001].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data that support the findings of this study are available from the sources identified in the manuscript.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A Definition of Pre- and Post-Period



^**PP	
Variable	Definition
Private information production variables	
CONSENSUS _{i,q}	The proportion of common information to total information in analysts' forecasts calculated using the methodology described in Barron et al. (2002). Specifically, it is calculated as $1 - D/V$, where D is the sample variance of individual forecasts around the mean forecast and V is the mean of the squared differences between individual forecasts and actual reported earnings. PRE_CONSENSUS (POST_CONSENSUS) is CONSENSUS calculated using analysts' quarter q earnings forecasts for firm i issued in the pre-period (post-period).
PRECISION _{i,q}	The precision of analysts' private information calculated using the methodology described in Barron et al. (2002). Specifically, it is calculated as (1 – CONSENSUS) * (1/V), where V is defined above. PRE_PRECISION (POST_PRECISION) is PRECISION calculated using analysts' quarter q earnings forecasts for firm i issued in the pre-period (post-period).
D_CONSENSUS _{i,q}	The difference between POST_CONSENSUS and PRE_CONSENSUS. RANK_D_CONSENSUS is the quartile ranking of D_CONSENSUS.
D_PRECISION _{i,q}	The difference between POST_PRECISION and PRE_PRECISION. RANK_D_PRECISION is the quartile ranking of D_PRECISION.
POST _{i,q}	An indicator variable equal to one if CONSENSUS (or PRECISION) is measured using forecasts issued in the post-period, and zero otherwise.
PIN _{i,q}	Probability of informed trading estimated using the methodology described in Easley et al. (2002). PIN_AD (PIN_NAD) is PIN estimated using days when early-announcing industry peers report earnings (no industry peers announce earnings). I exclude days when the firm itself report earnings or earnings guidance from the analysis. At least 60 non-missing observations are required to estimate PIN. This measure is estimated for each firm-year.
D_PIN _{i,q}	The difference between PIN_AD and PIN_NAD. RANK_D_PIN is the quartile ranking of D_PIN.
AD _{i,q}	An indicator variable equal to one if PIN is estimated using announcement days, and zero otherwise.
EDGAR_AD _{i,d}	The number of Edgar searches for firm i on day d when early-announcing peers report earnings. Only searches related to non-index pages (idx = 0), with file size greater than zero (size > 0) and file type being "htm" or "txt" (doctype = .htm or .txt) are included in the analysis.
EDGAR_NAD _{i,d}	The number of Edgar searches for firm i on day d when no industry peers announce earnings. I also exclude days when the firm itself reports earnings or guidance.
D_EDGAR _{i,d}	The difference between EDGAR_AD _{i,d} and the average of EDGAR_NAD in the same quarter. RANK_D_EDGAR is the quartile ranking of D_EDGAR.

Appendix B Variable Definitions

Variable	Definition
Information transfer variables	
RET_LO _{i,q}	The one-day market-adjusted excess return of late-announcing firm i over its own earnings announcement window in quarter q.
RET_LE _{i,d,q}	The one-day market-adjusted excess return of late-announcing firm i over early announcers' earnings announcement date d in quarter q.
RET_EO _{i,d,q}	The average of the one-day market-adjusted excess returns of all early announcers that announced earnings on day d in quarter q.
CLOSEPEER _{i,d,q}	An indicator variable equal to one if at least one early announcer on a certain day d is a close peer to late-announcing firm i in quarter q, and zero otherwise.
MIX _{i,d,q}	The negative of the absolute value of the difference between the percentage of positive and negative news of all early announcers on a given day d. Early announcer news is measured as the early announcer's one-day market-adjusted excess return on its own earnings announcement day. RANK_MIX is the quartile ranking of MIX.
DISP _{i,d,q}	The dispersion of early announcers' news on a given day. Early announcer news is measured in the same way as described above. RANK_DISP is the quartile ranking of DISP.
Other variables	
ACC _{i,q}	Total accruals calculated in the same way as in Sloan (1996) but on a quarterly basis.
HPSCORE _{i,q}	Product similarity score developed in Hoberg and Phillips (2010, 2016).
INSTOWN _{i,q}	Percentage of institutional ownership. Observations with missing values on INSTOWN is set to have a value of zero.
LAG1Q_RETLO _{i,q}	Late-announcing firm i's one-day excess return around its own earnings announcement in $q - 1$.
LAG4Q_RETLO _{i,q}	Late-announcing firm i's one-day excess return around its own earnings announcement in $\mathbf{q}-4$.
LOGACOV _{i,q}	The natural logarithm of one plus the number of analysts that have issued at least one forecasts or recommendations for a particular firm over the fiscal year.
LOGBM _{i,q}	The natural logarithm of book-to-market ratio.
LOG_NDAYS _{i,q}	The natural logarithm of the average number of days between the announcement date of the forecasts and firm i's earnings announcement date in current quarter q.
LOGSIZE _{i,q}	The natural logarithm of market capitalization.
RET6 _{i,q}	Late-announcing firm i's buy-and-hold six-month returns up to one week before its earnings announcement date in the current quarter q.
ROA _{i,q}	Return-on-asset, measured as earnings before extraordinary items divided by total assets.

Notes

¹ Unless otherwise noted, I use "intra-industry information transfer" and "information transfer" interchangeably in this paper.

² A detailed discussion of the definition and examples of "private information" is provided in Section 2.1.

- ³ Appendix A provides a graphical depiction of the timeline. More discussions about analysts' forecast consensus and precision as measures for private information production is provided in Section 3.2.1.
- ⁴ I exclude days when the firm makes its own earnings announcements or earnings guidance from the analysis. For more details on the research design and the validity of PIN as a measure for private information production, please refer to Section 3.2.
- ⁵ Future research could explore these potential boundary conditions to further refine our understanding of the dynamics of private information production in response to peer earnings announcements. However, this study focuses on establishing the general relationship, providing a foundation for future investigations into the nuances and contingencies of this phenomenon.
- ⁶ Appendix B provides detailed descriptions of these variables.
- ⁷ The underlying assumption for the PIN measure is that investors of the late announcers are able to collect, process, and trade on the early announcers' earnings news on the day of the announcements. This assumption is likely to be reasonable as prior research found that informed traders take only minutes to incorporate private information into stock prices (e.g., Bolandnazar et al., 2020). A similar logic also applies to the assumption underlying the calculation of the EDGAR search measure and the earnings news ambiguity measures in Section 5.
- ⁸ See Note 6.
- ⁹ Specifically, as the research question focuses on the information transfer within the industry, industry fixed effects can help isolate this by controlling for other factors affecting the industry as a whole. This allows me to more precisely estimate how the early announcer's news per se spills over to the late announcer's stock prices. However, firm fixed effects in this case would control for all time-invariant firm-specific characteristics that affect stock returns. This could inadvertently remove the very variation this paper is interested in studying, which is how the firm responds to its industry peers' earnings news.
- ¹⁰ The Pearson (Spearman) correlation between D_CONSENSUS and D_PRECISION was -0.717 (-0.640), and both were significant at the 1% level. This is comparable with the results reported in Table 2 of Barron et al. (2005).
- ¹¹ To ensure the robustness of the OLS regression analysis, I conducted a series of diagnostic tests to assess the model's assumptions. The (untabulated) results indicated that the assumptions of linearity, homoskedasticity, absence of multicollinearity, and timeseries stationarity were satisfied. Furthermore, I failed to find evidence that the model suffers from significant omitted variable bias. However, the normality assumption was violated for both CONSENSUS and PRECISION, raising concerns about potential bias in the OLS estimates. To address this issue, I employed quantile regression as a complementary analysis. This approach relaxes the normality assumption and provides a more robust estimation of the relationship between the variables of interest, further corroborating the findings of the OLS analysis. The results of the quantile regression are presented in Table 2, Panel B.
- ¹² Similar to the previous analysis, I conducted diagnostic tests to assess the assumptions of the OLS regression model. The (untabulated) results indicated that the assumptions of linearity, homoskedasticity, absence of multicollinearity, and time-series stationarity were satisfied. Additionally, there was no evidence of significant omitted variable bias. However, PIN violated the normality assumption. Thus, I employed quantile regression as a complementary analysis and present the results in Table 3, Panel B.
- ¹³ Diagnostic tests (untabulated) confirmed that the OLS regression model met the assumptions of linearity, homoskedasticity, absence of multicollinearity, and time-series stationarity. There was no evidence of omitted variable bias. Additionally, the normality of RET_LO supported the use of OLS.
- ¹⁴ Assessment of multicollinearity (untabulated) suggested that the regression coefficients were reliable.
- ¹⁵ In untabulated tests, the mean (median) of EDGAR_AD was 64.479 (19.000), while the mean (median) of EDGAR_NAD was 55.780 (16.000). The difference between the mean of EDGAR_AD and EDGAR_NAD was significantly positive (at 1% level), confirming the findings in Drake et al. (2015) that EDGAR search traffic for non-announcing firms increases when peers announce earnings.
- ¹⁶ The conjectures that late announcer investors' private information production increases when close peers announce earnings and when early announcers' earnings news has high ambiguity do not necessarily contradict each other. Prior research has documented both positive and negative information transfers from industry peers (e.g., Kim et al., 2008). Specifically, positive transfers are due to the commonality in business operations while negative transfers are due to competitive rivalry. Although close peers are more similar to the late-announcing firm in business operations, they are also more likely to be rivals. Thus, news from close peers may not have unambiguous implications for the late-announcing firm.
- ¹⁷ See Note 14.
- ¹⁸ In an untabulated analysis, I also calculated the EDGAR search traffic for the early announcers when the late announcers report earnings, and it had a mean (median) of 54.991 (17.000) with a standard deviation of 94.383. Univariate analysis suggested that there was no significant difference between the EDGAR search traffic for the early announcer on late announcers' reporting days and EDGAR_NAD, which is consistent with findings in prior research that the extent of information transfer is much stronger from the early announcer to the late announcer than vice versa (Hall et al., 2012).
- ¹⁹ Specifically, RANK_LIQCONSTR is the quartile ranking of the late announcer's liquidity constraint, measured as the debt-toequity ratio as of the end of the previous quarter; RANK_LOGACOV is the quartile ranking of investor attention to the late announcer, measured as one plus the number of analysts covering the firm in the previous quarter; RANK_LOGSIZE is the

quartile ranking of LOGSIZE; and RANK_HHI is the quartile ranking of the HHI index of the late announcer's four-digit SIC industry measured in the previous year.

References

- Balakrishnan, K., Shivakumar, L., & Taori, P. (2021). Analysts' estimates of the cost of equity capital. *Journal of Accounting and Economics*, 71(2–3), 101367. [CrossRef]
- Barron, O. E., Byard, D., & Kim, O. (2002). Changes in analysts' information around earnings announcements. *The Accounting Review*, 77(4), 821–846. [CrossRef]
- Barron, O. E., Harris, D. G., & Stanford, M. (2005). Evidence that investors trade on private event-period information around earnings announcements. *The Accounting Review*, 80(2), 403–421. [CrossRef]
- Blankespoor, E. (2019). The impact of information processing costs on firm disclosure choice: Evidence from the XBRL mandate. *Journal* of Accounting Research, 57(4), 919–967. [CrossRef]
- Blankespoor, E., deHaan, E., & Marinovic, I. (2020). Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics*, 70(2–3), 101344. [CrossRef]
- Bolandnazar, M., Jackson, R. J., Jiang, W., & Mitts, J. (2020). Trading against the random expiration of private information: A natural experiment. *Journal of Finance*, 75(1), 5–44. [CrossRef]
- Brown, A. B., Lin, G., & Zhou, A. (2022). Analysts' forecast optimism: The effects of managers' incentives on analysts' forecasts. *Journal of Behavioral and Experimental Finance*, 35, 100708. [CrossRef]
- Chou, H., Li, M., Yin, X., & Zhao, J. (2021). Overconfident institutions and their self-attribution bias: Evidence from earnings announcements. *Journal of Financial and Quantitative Analysis*, 56(5), 1738–1770. [CrossRef]
- Crane, A., Crotty, K., & Umar, T. (2023). Hedge funds and public information acquisition. *Management Science*, 69(6), 3241–3262. [CrossRef]
- Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, 53(6), 1839–1885. [CrossRef]
- Drake, M. S., Roulstone, D. T., Jennings, J., & Thornock, J. R. (2015). *The comovement of investor attention*. Working paper. Brigham Young University.
- Durnev, A., & Mangen, C. (2020). The spillover effects of MD&A disclosures for real investment: The role of industry competition. *Journal of Accounting and Economics*, 70(1), 101299.
- Dyer, T. A. (2021). The demand for public information by local and nonlocal investors: Evidence from investor-level data. *Journal of Accounting and Economics*, 72(1), 101417. [CrossRef]
- Easley, D., Hvidkjaer, S., & O'Hara, M. (2002). Is information risk a determinant of asset returns? *The Journal of Finance*, 57(5), 2185–2221. [CrossRef]
- Gallo, L. A., Sridharan, S. A., Ton, K., & Yohn, T. L. (2021). *Non-GAAP disclosures and investor uncertainty*. Working paper. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3766358 (accessed on 1 October 2024).
- Gao, M., & Huang, J. (2020). Informing the market: The effect of modern information technologies on information production. *The Review of Financial Studies*, 33(4), 1367–1411. [CrossRef]
- Gong, G., Qu, H., & Tarrant, I. (2021). Earnings forecasts and price efficiency after earnings realizations: Reduction in information asymmetry through learnings from price. *Contemporary Accounting Research*, 38(1), 654–675. [CrossRef]
- Hall, C., Sunder, J., & Sunder, S. V. (2012). *Tis the season for earnings! Analysis of information spillovers in earnings seasons*. Working paper. University of Arizona.
- Hand, J. R., Laurion, H., Lawrence, A., & Martin, N. (2021). Explaining firms' earnings announcement stock returns using FactSet and I/B/E/S data feeds. *Review of Accounting Studies*, 27, 1389–1420. [CrossRef]
- Hann, R. N., Kim, H., & Zheng, Y. (2019). Intra-industry information transfers: Evidence from changes in implied volatility around earnings announcements. *Review of Accounting Studies*, 24(3), 927–971. [CrossRef]
- Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies*, 23(10), 3773–3811. [CrossRef]
- Hoberg, G., & Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5), 1423–1465. [CrossRef]
- Hossain, M., Jansen, B., & Taylor, J. (2019). *Do analysts cater to investor information demand?* Working paper. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3480609 (accessed on 1 October 2024).
- Hung, C., & Lai, H. N. (2022). Information asymmetry and the profitability of technical analysis. *Journal of Banking and Finance*, 134, 106347. [CrossRef]
- Jegadeesh, N., Luo, J., Subrahmanyam, A., & Titman, S. (2023). *Short-term reversals and long-term momentum around the world: Theory and evidence*. Working paper. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4069575 (accessed on 1 October 2024).

- Kim, Y., Lacina, M., & Park, M. S. (2008). Positive and negative information transfers from management forecasts. *Journal of Accounting Research*, 46(4), 885–908. [CrossRef]
- Liu, B., Tan, K., Wong, S. M. L., & Yip, R. W. Y. (2022). Intra-industry information transfer in emerging markets: Evidence from China. *Journal of Banking and Finance*, 140, 106518. [CrossRef]
- Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of Financial Studies*, 22(1), 435–480. [CrossRef]
- Ramnath, S. (2002). Investor and analyst reactions to earnings announcements of related firms: An empirical analysis. *Journal of Accounting Research*, 40, 1351–1376. [CrossRef]
- Schauer, C., Elsas, R., & Breitkopf, N. (2019). A new measure of financial constraints applicable to private and public firms. *Journal of Banking and Finance*, 101, 270–295. [CrossRef]
- Schneemeier, J. (2023). Voluntary precision disclosure and endogenous market feedback. *Management Science*, 69(9), 4973–5693. [CrossRef]
- Securities and Exchange Commission. (2003). *What we do*. Available online: https://www.sec.gov/about/whatwedo.shtml (accessed on 1 October 2024).
- Sloan, R. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review*, 71(3), 289–315.
- Stoumbos, R. (2023). The growth of information asymmetry between earnings announcements and its implications for reporting frequency. *Management Science*, 69(3), 1323–1934. [CrossRef]
- Thomas, J., & Zhang, F. (2008). Overreaction to intra-industry information transfers? *Journal of Accounting Research*, 46(4), 909–940. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.