THE EFFECT OF FINANCIAL STATEMENT COMPARABILITY ON PRICE DISCOVERY

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Lingfeng Geng

May 2022

THE EFFECT OF FINANCIAL STATEMENT COMPARABILITY

ON PRICE DISCOVERY

Lingfeng Geng, Ph. D.

Cornell University 2022

I investigate the effect of financial statement comparability on the price discovery process. Using an input-based measure of comparability and the setting of earnings announcements, I document greater short-window price reactions to earnings news when firms have higher comparability in their financial statements. The new information is impounded into prices more quickly, and there is less post-earnings-announcement drift. Meanwhile, the relative order of earnings announcements does not influence the relation between comparability and price discovery. When comparability is high, investors are more likely to search for peer information before and during announcements. Taken together, this study provides empirical evidence that financial statement comparability reduces information processing costs and improves the speed of price discovery.

BIOGRAPHICAL SKETCH

Lingfeng Geng was born on October 16th, 1993, in Henan Province, China. His research interests revolve around the role of accounting information in capital markets and investors' decision making. Prior to joining the Johnson Ph.D. Program in 2017, Lingfeng studied at the University of Queensland, where he received his Bachelor of Commerce (first class Honours) Degree and earned the University Medal. He also received UQ Business School Honours Scholarship and Dean's Honour Roll. He received Byron E. Grote Johnson Professional Scholarship in 2019. His hobbies include snowboarding, basketball, and table tennis.

ACKNOWLEDGMENTS

After almost five years since I came to Cornell to pursue a Ph.D. in Accounting, the program is finally coming to an end. I ask myself: what if I had not come to Cornell? There might be a lot of possibilities, but none of them would be as challenging and self-fulfilling as this one. I want to take a moment to thank the people who offered a great deal of help and support along this journey.

First and foremost, I would like to express my deepest gratitude to the Chair of my special committee, Professor Luo Zuo. Luo has been such a great mentor for me in research and life, even before I came to Cornell. Just after I accepted the offer in February, Luo sent me many helpful materials to help me prepare for the transition to the Ph.D. program. He also encouraged me to participate in the MIT Asia conference even before the program started. Over the years, whenever I encountered setbacks and stresses, Luo would always provide his advice and encouragement. I have been and will always be learning from him on how to become a successful researcher who is hard-working, optimistic, and confident.

I am grateful to the co-chair and other members of my special committee for their comments and guidance in developing the dissertation and in the job market: Sanjeev Bhojraj, Warren Bailey, and Nicholas Guest. Sanjeev always helps me to think from a practical perspective: How does the question matter? Why would investors care? Warren's international finance seminar showed me the studies in international settings and led me to think about IFRS adoption and comparability. Nick and I have similar starting years at Cornell. He is a role model for me as a junior faculty, always working hard and thinking independently. I also want to thank all the Johnson professors who helped me during the Ph.D. process, including Robert Bloomfield, Ryan

Guggenmos, Robert Libby, Yao Lu, Kristina Rennekamp, Mani Sethuraman, Eric Yeung, and Xinyu Zhang.

I am also grateful to my cohorts in the Ph.D. program for making these years more enjoyable and less stressful. Although Kelvin is one year ahead of me, he is like my little brother. We talk about everything in life and research. I will never forget the weekly dinner or lunch with Ashish, Jun, and Rihuan. As the only student in my year, I am fortunate to have someone who is always there and willing to help. My appreciation also goes to Felipe, Chuchu, Manuela, Pat, Mike, Eunjee, Blake, Elisha, Jiawen, and Jin Hee. I could not imagine how these years would be without them.

In addition, I wish to thank Rani Hoitash, Udi Hoitash, Ahmet Kurt, and Rodrigo Verdi for their support and generously sharing the comparability data with me.

Finally, I am grateful for my parents and fiancée back in China. Their encouragement and support helped me start to pursue a Ph.D. degree. They are my motivations to keep learning and moving forward. Although thousands of miles apart, they always care about me and try to help me go through the ups and downs. My fiancée, Cece, is so intelligent and independent that she helps to make this difficult long-distance relationship work well while thriving in her career.

TABLE OF CONTENTS

BIOGRAPHICAL SKETCH iv
ACKNOWLEDGMENTS v
TABLE OF CONTENTS vii
1. Introduction 1
2. Related literature and Hypothesis Development 6
2.1 Studies on Financial Statement Comparability 6
2.2 Measurement of Financial Statement comparability 8
2.3 Main Hypotheses 9
3. Research Design 11
3.1 Estimating Financial Statement Comparability 11
3.2 Estimating the Speed of Price Discovery 12
3.3 Measuring the Order of Earnings Announcements 13
3.4 Estimating Fundamental Information Acquisition 14
3.5 Empirical Model 14
4. Sample and Descriptive Statistics 15
4.1 Sample 15
4.2 Descriptive Statistics 16
5. Main Results 17
5.1 Financial Statement Comparability and Price Responses to Earnings News 17
5.2 Financial Statement Comparability and Intraperiod Timeliness 17
5.3 Financial Statement Comparability and Post Earnings Announcement Drift 18
5.4 The Influence of Relative Orders of Earnings Announcements 19
5.5 Financial Statement Comparability and Fundamental Information Acquisition 20
6. Additional Analyses and Robustness Tests 21
6.1 Time-Series Change of the Relation 21
6.2 Financial Statement Comparability and Trading Volume 22
6.3 Financial Statement Comparability and Short Seller 23
6.4 Financial Statement Comparability and Algorithmic Trader 25
6.5 Controlling for Accrual Quality, Product Similarity, and Accounting Complexity 27
6.6 Other Robustness Tests 28
7. Conclusion 29
Appendix: Variable Definitions 34
Main Tables 36

"Users' decisions involve choosing between alternatives…information about a reporting entity is more useful if it can be compared with similar information about other entities and about the same entity for another period or another date."

– FASB, Concept Statement No.8

1. Introduction

Comparability is defined as "the qualitative characteristics that enable users to identify and understand similarities in, and differences among, financial statement items" (FASB 2010). It is one of the four enhancing qualitative characteristics of useful financial information. [1] The two fundamental characteristics of useful information are relevance and faithful representation. Some may argue that as long as the information is relevant and faithfully represented, comparability is only a "nice-to-have" quality of information and not as important. However, this is only true when there are no information processing costs. According to Blankespoor, de Haan, and Marinovic (2020), the existence of disclosure processing costs (awareness costs, acquisition costs, and integration costs) means that disclosures can be a form of costly private information, and disclosure processing is an optimization problem in which investor allocate scarce processing resources across multiple disclosures. In this case, comparability becomes extremely important as it helps investors make more effective comparisons between peer firms and reduce disclosure processing costs.

[1] The other three enhancing characteristics are: verifiability, timeliness, and understandability. Verifiability enables different observers to reach consensus that a particular description is a faithful representation. Timeliness means having information available to decision makers in time. Understandability means that information is presented clearly and concisely to make it understandable for users who have a reasonable knowledge of business and economic activities.

In this paper, I investigate the influence of financial statement comparability[2] on the price discovery process around earnings announcements. I argue that comparability reduces disclosure processing costs by providing better benchmarks and facilitating information transfer among comparable firms. Therefore, I hypothesize that comparability accelerates price discovery after the earnings announcements. I use the setting of quarterly earnings announcements as they are among the recurring firm events with the greatest average effects on stock prices, given the new information they contain. Also, quarterly earnings announcements are ubiquitous, which provides rich cross-section variations and minimal selection effects over which information events are observed. A new input-based comparability measure (following Hoitash, Hoitash, Kurt, and Verdi 2018) is adopted in my study. It measures the extent to which Compustat line items in a firm's financial statements are similar to those reported by peer firms. It complements the more widely used output-based measure of comparability, which assumes the information is impounded into prices at the same rate between different firms. The implicit assumption of market efficiency limits researchers use of output-based measure to examine the relation between comparability and price discovery. More details about the measure construction and its relative advantage are discussed in Section 3.1.

To test my first hypothesis that comparability accelerates price discovery after earnings news, I first examine the influence of financial statement comparability on short-window price reaction to earnings news. By regressing the announcement date abnormal return (and alternative short-window abnormal returns) on comparability and its interaction with standardized unexpected earnings (*SUE*), I find that firms with higher comparability experience stronger immediate price

[2] In this study, I use financial statement comparability and comparability interchangeably.

reactions to earnings news, which provides some preliminary evidence in support of my first hypothesis.

Next, I test the hypothesis with a measure of *Intraperiod Timeliness*. It is a widely used measure in accounting and finance studies (Butler, Kraft, and Weiss 2007; Bushman, Smith and Wittenberg-Moerman 2010; Twedt 2016; Guest 2021) to estimate the speed at which new information is impounded into stock prices. My results show that a one-standard-deviation increase in comparability is associated with a 3.67% standard deviation higher IPT, supporting my conjuncture that higher comparability leads to a higher speed of price discovery. I also try to complement my results with post-earnings-announcement-drift (PEAD). I find that a one-standard-deviation increase in comparability leads to a 0.85% decrease in the hedge portfolio returns, indicating a smaller PEAD for firms with higher comparability.

My second hypothesis tests the influence of the relative order of earnings announcements. If a firm announces its earnings relatively early, there is less information from peer firms (as it is not yet available) for the investors to compare and use as benchmarks. Thus, the benefits of comparability in accelerating price discovery may be weaker, and vice versa. I find no evidence of the relative order of earnings announcement influencing the relation between comparability and price discovery. It seems that investors use both concurrent and historical peer information to facilitate the processing and analysis of the new information, which makes the relative order of earnings announcement less important.

My third hypothesis examines investors' information searching activities before earnings announcements. I argue that peer information becomes more useful and decision-relevant. I find that investors are more active in searching for peer information before (during) earnings

announcements when focal firms have higher comparability. However, the information acquisition about the focal firm is not influenced by its comparability.

In the additional analyses, I first look at the time-series change of the relation between comparability and price discovery. I find that the relation becomes stronger in later years. Holding comparability constant, the increase in announcement response and *Intraperiod Timeliness*, and decrease in PEAD is more significant in more recent years.

Next, I examine the relation between (abnormal) trading volume and comparability. I find that firms with higher financial statement comparability have higher (abnormal) trading volume around earnings announcements. This is consistent with the argument that comparability helps reduce the information processing costs, encouraging more investors to process and trade on the new information in the earnings announcements.

I then conduct analyses regarding financial statement comparability and two groups of market participants, short sellers, and algorithmic traders. Both of them are important constituents of capital markets. I find that comparability is associated with a lower level of short interest, suggesting that comparability, by facilitating information transfer, limits managers' incentive and ability to hoard bad news. There will be lower payoffs from the short position. As a result, short sellers tend to avoid firms with high comparability. There is no significant relation between the level of algorithmic trading and comparability. However, I find some evidence that a relatively lower level of algorithmic trading leads to stronger effects of comparability on the speed of price discovery. This suggests that algorithmic traders, on average, put more focus on hard information, mathematical models, etc., and make less use of financial statements compared with human investors.

Lastly, I conduct a series of sensitivity tests to ensure the robustness of my results. I control for accrual quality (Kothari, Leone, and Wasley 2005), product similarity (Hoberg and Philips 2016), and accounting complexity (Hoitash and Hoitash 2018); use different fixed effects specifications; and convert the comparability score into decile rankings. I also try to address the concern of endogeneity by orthogonalizing variables that possibly influence firms' financial statement comparability. My results remain qualitatively similar.

My study makes several contributions. Firstly, prior studies on financial statement comparability find the benefits of comparability for analysts (De Franco et al. 2011), debt markets (Kim, Kraft, and Ryan 2013), auditors (Zhang 2018), managers acquisition decision making (Chen, Collins, Kravet, and Mergenthaler 2018) and corporate innovation (Chircop, Collins, Hass, and Nguyen 2020). There are limited studies on the relation between comparability and price discovery. One of the reasons is the widely-used output-based measure by De Franco et al. (2011). They implicitly assume that information is impounded into the price at the same rate across firms, which naturally limits the possibility of testing the relation between comparability and price discovery. By using the input-based measure that relaxes the assumption of market efficiency, I provide direct evidence as to how comparability improves price discovery, one of the fundamental functions of stock markets. My study also has policy implications for standard setters and regulators. For example, non-GAAP disclosures have become more and more prevalent in recent years. Bentley, Christensen, Gee, and Whipple (2018) find that non-GAAP earnings are available for 60% of firms in 2013. One major concern with non-GAAP earnings is the lack of comparability across firms, and firms might opportunistically benefit at investors' expense. My study can serve as a reminder to the regulator to make careful tradeoffs between non-GAAP earnings and comparability. Despite being one of the enhancing characteristics instead of fundamental characteristics, comparability is

not simply a “nice-to-have” quality of financial information. Instead, it has great capital market implications considering information processing costs. Lastly, my results have practical implications for managers regarding short sellers.

The remainder of the paper is organized as follows. Section 2 summarizes prior studies on financial statement comparability and develops the main hypotheses for the paper. Section 3 specifies the empirical design to test the hypotheses, followed by Section 4, where I describe the sample and data sources. I present my main results in Section 5. Section 6 shows additional analyses and robustness tests. Section 7 summarizes and offers concluding remarks.

2. Related literature and Hypothesis Development

2.1 Studies on Financial Statement Comparability

There are two streams of research in the studies of financial statement comparability. The first large stream of studies focuses on the comparability problems that arise from the adoption of International Financial Reporting Standards (IFRS) in different countries, in most cases, the European ones. After the mandatory adoption of IFRS for EU countries in 2005, the financial statement comparability across various countries was expected to adjust to the new reality. DeFond, Hu, Hung, and Li (2011) document that foreign mutual fund ownership increases in European firms when they mandatorily adopt IFRS, since the adoption improves accounting comparability of these firms. Barth, Landsman, Lang, and Williams (2012) examine if IFRS-based accounting numbers are comparable to U.S. GAAP-based ones using firms in 27 IFRS adopting countries and the United States. They find that firms’ accounting numbers in IFRS adopting countries become more comparable to those of U.S. firms, and this increase is more pronounced for mandatory adopters. Yip and Young (2012) emphasize that the increased similarity of similar firms, as well as the decreased similarity of dissimilar firms, can both improve overall financial statement

comparability. Their results suggest that mandatory IFRS adoption improves cross-country accounting comparability by making similar things look more alike without making different things look less different. Brochet, Jagolinzer, and Riedl (2013) examine the indirect capital market benefits brought by IFRS adoption through enhanced financial statement comparability. They find that the improved comparability from IFRS adoption reduces the ability of insiders to exploit private information.

The second important stream of comparability research focuses on the determinants and consequences of financial statement comparability. For example, Francis, Pinnuck, and Watanabe (2014) find that companies audited by the same auditors display more comparable financial statements by examining the auditor-fixed effects. They identify economic institutions as a determinant of accounting comparability. Imhof, Seavey, and Watanabe (2018) find that financial statement comparability is decreasing in the proprietary costs of financial reporting, emphasizing the importance of competition. As for the benefits of financial statement comparability, De Franco, Kothari, and Verdi (2011) investigate the effect of accounting comparability on analyst coverage and forecast properties. They find that the higher accounting comparability of the followed firm is associated with more analyst coverage, higher forecast accuracy, and less forecast dispersion. It is one of the most influential papers about financial statement comparability because of the introduction of an output-based methodology to measure comparability. This method has been adopted widely by later studies and will be discussed in detail in the next section. Kim, Kraft, and Ryan (2013) turn to the debt market and find that financial statement comparability reduces debt market participants' uncertainty about and pricing of firms' credit risks. Chen, Collins, Kravet, and Mergenthaler (2018) find that acquirers make better acquisition decisions when target firms' financial statements exhibit greater comparability with industry peer firms. Other benefits of

financial statement comparability include lower ex-ante crash risk (Kim, Li, Lu, and Yu 2016), lower cost of equity capital (Imhof, Seavey, and Smith 2017), lower audit effort, and better audit outcomes (Zhang, 2018), greater innovative efficiency (Chircop, Collins, Hass, and Nguyen 2020). The common theme of these studies is that comparability facilitates information transfer among comparable firms, such that financial statement users make sharper inferences about their economic similarities and differences.

2.2 Measurement of Financial Statement comparability

Before De Franco et al. (2011), early papers on accounting comparability use input-based approaches to measure comparability, most of which involves counting, weighting, and aggregating accounting choices to create comparability indices (Kvaal and Nobes 2012). De Franco et al. (2011) recommend that the way economic events map into earnings be used as an indicator for comparability. It is based on the premise that "for a given set of economic events, two firms have comparable accounting systems if they produce similar financial statements." They use stock returns as a proxy for economic events and earnings as a proxy for the financial statement output. They estimate the parameters of this function through firm-specific time-series regressions. Holding stock returns (economic events) constant, a pairwise comparability score is the difference between the expected earnings (financial statement output) of the two firms under consideration. Then, pairwise measures between a focal firm and all its industry peers are combined into firm-year-specific summary measures. The implicit assumption of the measure is that economic information is impounded into prices at the same rate across different firms. Compared with the traditional input-based measures of comparability, the output-based measure does not involve the manual selection of accounting choices and corresponding weighting, which makes it more

objective. The sample size is bigger as input-based measure involves hand collecting data from financial reports. Most empirical studies on comparability use the output-based measure from De Franco et al. (2011) or its modifications. Kim et al. (2013) propose their own measure of comparability specifically designed for debt market participants. It is defined as the negative value of the variability of Moody's adjustments affecting the interest-coverage ratio or the adjustments for non-recurring income items within an industry-peer group. A lower heterogeneity of the adjustments is assumed to indicate higher comparability.

2.3 Main Hypotheses

Based on the framework from Blankespoor, deHaan, and Marinovic (2020), disclosure processing costs affect investor information choices, trades, and market outcomes. The processing costs include awareness costs (monitoring for a disclosure's existence), acquisition costs (extracting signals from disclosure), and integration costs (analyzing implications for firm value). I argue that comparability reduces disclosure processing costs by influencing the integration costs and acquisition costs. When a firm is more comparable with its industry peers, investors have a better benchmark against which to evaluate a firm's relative performance (Young and Zeng 2015). By benchmarking against firms with high comparability (holding accounting system constant), investors make sharper inferences at a lower cost, and the integration costs of signals become lower. In addition, enhancing the comparability of disclosures across firms can result in efficiency gains by reducing investors' duplication of information production (Dye and Sunder 2001). Also, financial statement comparability increases the overall quantity and quality of information available (De Franco et al. 2011). Taken together, comparability helps to reduce disclosure processing costs, improves firms' information environment, which leads to faster reaction to new

information (earnings news in the setting of earnings announcements) and faster price discovery. Stated in an alternative form, my first hypothesis is as follows:

H1: Ceteris paribus, the speed of price discovery is higher for firms with greater financial statement comparability.

The order in which firms announce earnings might be an important factor influencing the relation between comparability and price discovery. As argued above, comparability reduces disclosure processing costs by providing better benchmarks and facilitating information transfer among comparable firms. If a firm announces its quarterly earnings relatively early compared with its peers, its investors will have less information (as it is not yet available) for benchmarking. On the other hand, if a firm is a late announcer, the investors will have more information from its peer firms that announce before the focal firm. This suggests that the benefits of financial statement comparability on price discovery will be stronger for firms that announce their earnings relatively late. However, it is also possible that investors not only use concurrent information to make inferences but also learn from historical peer information. In this case, the relative timing of earnings announcements becomes less important. Overall, it remains an empirical question whether the relative order/timing of earnings announcements influences the relation between comparability and price discovery. My second hypothesis, stated in an alternative form, is as follows:

H2: The relation between financial statement comparability and the speed of price discovery is stronger for firms that are relatively late announcers.

Theoretically, comparability helps investors find better benchmarks and facilitate information transfer among comparable firms. From investors' perspective, to take advantage of a

firm's financial statement comparability, they are more likely to search for information about its peer firms before the focal firm's earnings announcement. In this way, there will be more peer information for the investors to compare and help them process the earnings news. On the other hand, if a firm's financial statements have low comparability, peer firms' information becomes less useful to the investors, and there will be less information searching before earnings announcements. My third hypothesis, stated in an alternative form, is as follows:

H3: For firms with higher financial statement comparability, there are more fundamental information searching activities for peer firms before earnings announcements.

3. Research Design

3.1 Estimating Financial Statement Comparability

I use an input-based measure of financial statement comparability following Hoitash, Hoitash, Kurt, and Verdi (2018), who emphasize the comparability of the line items reported on firms' financial statements.

The comparability measure is constructed in four steps. First, an annual reference point vector that includes all the non-missing relevant financial statement data items (relating to either the balance sheet, the income statement, or the statement of cash flow) reported in Compustat for a given fiscal year (1 ×N items, where N may differ across fiscal years). Second, firm-year-specific data item assessment vectors (1 × N) are created by assigning the value of 0 for items that are missing and 1 for items that are not.

Third, firm-year-specific assessment vectors are used to perform annual pairwise comparisons of the reported Compustat items for a focal firm and each of its industry peers,

resulting in pairwise comparability scores. [3] The pairwise comparability score is calculated using the Jaccard coefficient, which is the size of the intersection divided by the size of the union of the two sets. [4] In this setting, it is calculated as the number of overlapping Compustat items between the two firms divided by the number of total unique Compustat items reported by both firms. Fourth, an annual firm-level comparability score is calculated by averaging pairwise comparability scores across all industry peers of a focal firm. This score is my main measure of financial statement comparability (comparability SIC or comparability TNIC depending on the method of finding industry peers). The comparability measure can range between 0 (no comparability) and 1 (perfect comparability).

Compared with the output-based measures (De Franco et al. 2011) that primarily capture income statement comparability, this measure is more comprehensive as it also considers the balance sheet and the cash flow statement. Also, output-based measures assume that the rate at which economic information is incorporated into prices is the same across firms, which may not necessarily be true. This measure has no such concern. Compared with the traditional input-based approach, this measure does not involve hand collecting data and manually choosing accounting choices and their weights in constructing indices, making it more objective.

3.2 Estimating the Speed of Price Discovery

[3] The industry peers are defined at the 2-digit SIC level. Alternatively, a textual-based network industry classification (TNIC) for finding industry peers. The TNIC classification is proposed by Hoberg and Phillips (2016), who identify peer groups based on the similarity in firms' product description in 10-K filings. TNIC industries are dynamic, and allow for same firms to have different peers in a given year and over time. As a result, there are two measures of comparability, namely comparability SIC and comparability TNIC, using different industry classification to construct the comparability score.

[4] The Jaccard coefficient (Anderberg 1973) is defined as $J(A,B) = \frac{|A \cap B|}{|A \cup B|}$.

I use an *Intraperiod Timeliness* (IPT) metric to capture the speed with which new earnings information is impounded into price over a given period, which is widely used in prior finance and accounting studies (Butler, Kraft, and Weiss 2007; Bushman, Smith and Wittenberg-Moerman 2010; Twedt 2016; Guest 2021). IPT estimates the speed of the price response over day [0,5], relatively to the earnings announcement using an area-under-the-curve approach. Specifically, for each of day zero to five, I calculate the cumulative abnormal return from day zero through day t ($CAR_{i,t}^{[0,t]}$). The calculation of cumulative abnormal returns can be found in the Appendix. I then plot these daily cumulative returns, scaled by the total cumulative return for the day [0,5] period, to create a curve that reflects the speed of price discovery. The IPT metric is the area under the curve, with larger values indicating a faster price reaction to earnings news. If financial statement comparability helps to reduce information processing costs, new information should be impounded into the stock price more quickly, and the IPT metric should be higher for the firm.

$$IPT_{i,t} = \sum_{j=0}^{4} \frac{CAR_{i,t}^{[0,j]}}{CAR_{i,t}^{[0,5]}} + 0.5 \qquad (1)$$

3.3 Measuring the Order of Earnings Announcements

Following Noh, So, and Verdi (2021), my measure of the earnings announcement timing is "EA Order," defined as the ratio of n over N, where N is the number of firms with the same fiscal period end within the same SIC industry, and n is the ranking of a given firm's earnings announcement timing among N firms. I do not differentially rank earnings announcements on the same day based on their exact timing because time is more likely discretionary and difficult to measure cleanly (due to missing timestamps/ gaps in the timing of initial press release vs. detailed discussion during conference calls). I assign the same ranking to all firms announcing earnings on

the same day. A higher value of EA Order signals the earnings announcement is later relative to peer firms.

3.4 Estimating Fundamental Information Acquisition

My measure of fundamental information acquisition (FIA) before earnings announcements is the web traffic on the SEC's EDGAR servers (Lee, Ma, and Wang 2015; de Haan, Shevlin, and Thornock 2015). This measure provides insights into how much and when financial information of firms is being acquired by investors. The cumulative EDGAR pre-earnings announcement search volume is defined as:

$$ESV_{i,t}^{[T_0,T_1]} = \sum_{k=T_0}^{T_1} ESV_{i,t}^{k} \qquad (2)$$

where $ESV_{i,t}^{k}$ is that total non-robotic EDGAR downloads across all disclosures for each day k relative to the earnings date. A higher value of ESV indicates more information acquisition activity before earnings announcements. To calculate the FIA of peer firms, I find the firms that are most comparable to the focal firm within the SIC two-digit industry (top 20)[5] based on the pairwise comparability score. Then, $Peer\_ESV_{i,t}^{[T_0,T_1]}$ can be calculated as the sum of all the comparable peers' ESV. The EDGAR server data used for the construction of ESV metric is accessed through the SEC website and compiled following Ryans (2017).[6]

3.5 Empirical Model

I use below baseline model to investigate whether financial statement comparability affects price discovery:

[5] I can use top 4, top 10 most comparable firms. The results remain quantatitively similary.
[6] This is publicly available at http://www.jamesryans.com/.

$$Intraperiod\ Timeliness_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \beta X_{i,t} + \varepsilon_{i,t} \qquad (3)$$

where i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects, respectively; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements. These variables include *Size*, *Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss*. The calculation of each of the control variables can be found in the Appendix. Standard errors are clustered at the firm level. The coefficient of interest is γ_1.

In the case where the dependent variable is CAR, I use the model below:

$$CAR_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\, SUE_{\ i,t} + \gamma_3\left(Comparability_{i,t} \times SUE_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t} \qquad (4)$$

where SUE is the decile rank of the standardized unexpected earnings. The calculation of SUE can be found in the Appendix. Other specifications are similar to Equation (1), and the coefficient of interest is γ_3.

4. Sample and Descriptive Statistics

4.1 Sample

My sample period is from 1996 to 2015. For the comparability sample, Hoitash, Hoitash, Kurt, and Verdi (2018) start with the universe of companies that filed 10-K reports with the SEC. They remove holding firms, ADRs and limited partnerships, and financial firms. They also remove industries with less than ten firms based on 2-digit SIC in a given fiscal year, yielding 79,230 firm-years. [7] Next, I use data from IBES and Compustat to construct a sample of firms' quarterly

[7] I thank Rodrigo Verdi for graciously sharing their codes of output-based comparability measure with me.

earnings announcements over the same period. My basic sample requirements are that the firm-quarter has sufficient information to identify the earnings announcement date, earnings surprise, and abnormal stock returns. I require that each earnings announcement date from IBES be the same as the date provided by Compustat. I use timestamps from IBES to identify after-hour announcements and set day 0 to the following trading day. IBES also provides data about analysts' earnings forecasts, which is used to calculate SUE. Daily price, volume, and return data around each earnings announcement is obtained from the Center for Research in Security Prices (CRSP). Quarterly and yearly accounting information about the firm, short seller data are from Compustat. After merging comparability sample and earnings announcement sample, I have a total of 72,468 firm-quarter observations. The number of observations entering into my regression will vary and is usually smaller because of missing dependent and control variables.

4.2 Descriptive Statistics

Table 1 reports the descriptive statistics for the primary variables used in my analysis. Variables are defined in Appendix. All variables are winsorized at 1st and 99th to reduce the influence of outliers. The mean and standard deviation of *Comparability SIC* (*Comparability TNIC*) are 0.65 (0.63) and 0.04 (0.04), respectively, which are close to those in Hoitash, Hoitash, Kurt, and Verdi (2018). The average $CAR^{[0,1]}$ is 0.11% while the average $CAR^{[2,15]}$ is 0.16%. IPT has a mean of 3.78 and a standard deviation of 2.6, which are close to those in Blankespoor, deHaan, and Zhu (2018). The average number of EDGAR downloads for peer firms around earnings announcement is 527, and this number becomes 2,458 if I move the measurement window to 10

days before the earnings announcements. All other variables are of reasonable variation compared with prior literature. [8]

5. Main Results

5.1 Financial Statement Comparability and Price Responses to Earnings News

Before formally testing H1 using IPT metrics, I try to provide preliminary supporting evidence by examining the short-window price response to new information in earnings news. I run the regression based on Equation (5), using $CAR_{i,t}^{[0,1]}$, $CAR_{i,t}^{[0,2]}$, $CAR_{i,t}^{[0,3]}$ as the dependent variables. A positive interaction term between Comparability and SUE indicates a market reaction to earnings news, holding the magnitude of surprise constant. Note that I code earnings surprised into deciles, which are then adjusted by dividing the rank by nine and subtracting 0.5. Therefore, when regressing the cumulative abnormal return on the *SUE*, the slope coefficient is an estimate of the hedge portfolio (long good-news firms and short bad-news firms) return. The results are reported in Table 2. From Column (1) to Column (6), all the interaction terms between comparability and SUE are positive and statistically significant, suggesting that investors will have a stronger (quicker) reaction to earnings news from firms with higher comparability. [9] This provides some preliminary evidence that comparability help investors process the information more quickly.

5.2 Financial Statement Comparability and Intraperiod Timeliness

[8] For *Size, Book-to-Market, and No. Analysts*, I present the raw number for more straightforward interpretation. However, their natural logarithm transformations are used in the regression analyses.

[9] Note that the coefficients for SUE are consistently negative and significant. This only means that when comparability is equal to 0, the hedge portfolio return is negative, which is rarely the case (comparability is only equal to 0 when the firm has no over-lapping Compustat items with its industry peers). We need to consider the interaction terms when trying to find the main effect of the variable.

Table 3 present the regression results using Equation (3). In Columns (1) and (3), I run the regression with only firm fixed effects and year-quarter fixed effects. The coefficients for *Comparability SIC* and *Comparability TNIC* are 1.5 and 1.102, significant at 1% level, respectively. To address the concern that the faster reaction to earnings surprise of high-comparability firms may be due to omitted variables that happen to be correlated with comparability and IPT, I add in control variables as specified in Equation (5) in Column (2) and (4). The addition of control variables does not subsume the significant relation between comparability and IPT. In terms of economic significance, a one-standard-deviation increase in *Comparability SIC* (*Comparability TNIC*) is associated with a 3.67% (1.9%) standard deviation higher IPT. The results support my hypothesis that comparability helps to reduce information processing costs, which leads to a higher speed of price discovery (higher IPT). [10]

5.3 Financial Statement Comparability and Post Earnings Announcement Drift

One of the explanations for the existence of PEAD is that investors underestimate the implications of current earnings for future earnings, and their underreaction is corrected at future earnings announcement dates. The under-react explanation suggests that the magnitude of PEAD is influenced by the speed with which investors incorporate the implications of current earnings into their expectations of future earnings (Bernard and Thomas 1989; Ball and Bartov 1996). If comparability indeed helps to reduce information processing costs, the magnitude of PEAD should be smaller for firms with high accounting comparability. Following prior studies (e.g., Livnat and Mendenhall 2006), I use standardized unexpected earnings (SUE) as a proxy for the market's

[10] In the main analyses, IPT is constructed over day [0,5] relative to the earnings announcement. The results remain similar if I construct IPT over day [0, 10].

directional surprise to earnings information. I use Equation (5) and use $CAR_{i,t}^{[2,10]}$, $CAR_{i,t}^{[2,15]}$, $CAR_{i,t}^{[2,20]}$ as dependent variables.[11]

The results are presented in Table 4. Columns (1), (3), and (5) present the results when comparability is constructed using SIC industry classification. Comparability based on TNIC classification is used in columns (2), (4), and (6). Across all columns, the interactions between comparability and SUE remain negative and statistically significant at 1% level. As discussed in 5.1, the slope coefficient for SUE is an estimate of the hedge portfolio return. According to Columns (5) and (6), a one-standard-deviation increase of *Comparability SIC* (*Comparability TNIC*) leads to a 0.85% (0.71%) decrease in the hedge portfolio return. This is economically significant. Overall, the results suggest that higher comparability is associated with a smaller magnitude of PEAD, which lends support to Hypothesis 1.

5.4 The Influence of Relative Orders of Earnings Announcements

To test *Hypothesis 2*, I run the following regression:

$$\begin{aligned} CAR_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\, SUE_{\ i,t} + \gamma_3\, EA\ Order_{\ i,t} \\ + \gamma_4\left(Comparability_{i,t} \times SUE_{i,t} \times\ EA\ Order_{i,t}\right) \\ + \gamma_5\left(Comparability_{i,t} \times\ EA\ Order_{i,t}\right) + \gamma_6\left(Comparability_{i,t} \times SUE_{i,t}\right) \\ + \gamma_7\left(SUE_{i,t} \times\ EA\ Order_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t} \qquad (5) \end{aligned}$$

$$Intraperiod\ Timeliness_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2 EA\ Order_{\ i,t} +$$

$$\gamma_3\left(Comparability_{i,t} \times\ EA\ Order_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t} \quad (6)$$

[11] The results remain roboust when I use the cumulative abnormal returns between two consecutive earnings announcement dates.

The specifications are similar to Equation (3) and (4), and the coefficient of interest is γ_4 and γ_3 respectivley. A positive γ_4 (γ_3) means the relation between comparability and the speed of price discovery is stronger for firms that announce their earnings relatively late compared with peer firms.

The results are presented in Table 5. Columns (1), (3), (5) present the results when comparability is constructed using SIC industry classification. Comparability based on TNIC classification is used in columns (2), (4), and (6). When looking at immediate market response and PEAD, all the coefficients of interests are statistically insignificant except for column (1). While comparability continues to be positively associated with *Intraperiod Timeliness*, the coefficients of the interaction terms remain statistically insignificant across columns.[12] To conclude, there is no systematic evidence that the relative order of earnings announcements influences the relation between comparability and the speed of price discovery, which is consistent with the argument that investors can learn and compare both concurrent and historical information of peer firms, making the order of earnings announcement not so important.

5.5 Financial Statement Comparability and Fundamental Information Acquisition

To test *Hypothesis* 3, I use Equation (3) and replace the dependent variable with my measures of FIA before earnings announcements. Table 6 presents the regression results. Columns (1) and (3) present the results when the dependent variable is $Peer\_ESV^{[-10,1]}$. The coefficients for *Comparability SIC* and *Comparability TNIC* are statistically significant, suggesting that investors indeed search for more peer firms' information before earnings announcement when the firm has higher comparability in its financial statements. Economically speaking, a one-standard-deviation

[12] The results remain similar when I use different interval specifications.

increase in *Comparability SIC* leads to an increase of 208.8 in the total number of EDGAR downloads of peer firms in the 10-day pre-announcements window (around earnings announcements). The effects become weaker if I only look at the 3-day window around earnings announcement as reflected by Columns (2) and (4). In Column (5) to (8), I replace the dependent variable with $ESV^{[-10,1]}$ and $ESV^{[-1,1]}$, the information acquisition measure for the focal firms. The coefficients for comparability remain statistically insignificant. Taken together, the results in Table 6 suggest that financial statement comparability influences investors' information acquisition decisions regarding peer firms before earnings announcements. When focal firms have higher comparability, investors tend to search for more information about peer firms so that comparability can help them process the earnings news for the focal firm. However, comparability does not influence information acquisition decisions about the focal firms before earnings announcements.

6. Additional Analyses and Robustness Tests

6.1 Time-Series Change of the Relation

I first look at how the relation between Comparability and price discovery change over time. Ex ante, whether the relation will become stronger or weaker is unclear. Modern information technologies have fundamentally changed the way financial data is communicated to, and processed by, investors (Goldstein, Yang, and Zuo 2022). On one hand, with the development in modern technology and its applications in corporate disclosures (e.g., implementation of EDGAR system, adoption of XBRL, corporate twitter accounts, etc.), it is easier for firms to disseminate new information and for investors to collect information from difference sources. As a result,

comparability in financial statements might become less important in more recent years. On the other hand, with the new technologies, investors might be able to shift a significant amount of resources from data collection to data analysis (Blankespoor, Miller, and White 2014), which enables them to extract more relevant information from the comparable disclosures.

To examine the change of the relation over time, I re-estimate all the tests for my Hypothesis 1 with the addition of interaction terms with *Early*, which is a dummy variable defined as 1 for years before 2005 and 0 otherwise[13]. The results are presented in Table 7. Columns (1) and (2) present the results when the dependent variable is $CAR^{[0,2]}$ while the dependent variable is $CAR^{[0,60]}$ in columns (3) and (4). Lastly, columns (5) and (6) show results for the measure of *Intraperiod Timeliness*. Out of the 6 columns, there are significant results in 5 columns showing that the relation between comparability and price discovery becomes stronger in more recent years. Ceteris paribus, there are stronger immediate market reactions to earnings news, smaller magnitude of PEAD, and higher value of *Intraperiod Timeliness* in the years after 2005. The findings make my previous results more relevant to investors and companies.

6.2 Financial Statement Comparability and Trading Volume

In this section, I investigate the relation between (abnormal) trading volume and Financial Statement Comparability. Prior analytical research suggests that trading volume can be caused by disagreement among investors (Karpoff 1986; Kim and Verrecchia 1991,1994). Beaver (1968) argued that trading volume reactions reflect a lack of consensus regarding the appropriated price of the firm's shares. He further asserted that trading volume reactions capture changes in the expectations of individual investors while price reactions reflect changes in the expectations of the

[13] The results hold when I change the cut-off year to later or earlier years.

market as a whole. If financial statement comparability helps reduce disagreement among investors, there should be lower (abnormal) trading volume for firms with high comparability. On the other hand, investors have limited attention and thus cannot process all available information when making trading decisions (Hirshleifer and Teoh 2003). If information is relatively costly to process, then fewer investors will process and trade on the information (Grossman and Stiglitz 1980; Bloomfield 2002). Thus, if comparability indeed helps reduce information processing costs, it will encourage the investors to process and trade on the new information from the earnings announcement, leading to a higher trading volume. I use a regression similar to Equation (3), replacing dependent variables with (Abnormal) Trading Volume. Trading Volume is the average daily trading volume of the three-day window around earnings announcement ($Vol^{[-1,1]}$). I also calculate the average trading volume for the control period ($Vol^{[-22,-2]}$). Abnormal Trading Volume is the difference between the two ($Vol^{[-1,1]}$- $Vol^{[-22,-2]}$).

Table 8 reports the regression results. Columns (1) and (2) present the results when the dependent variable is $Vol^{[-1,1]}$ whereas Columns (3) and (4) present the results when the dependent variable is *Abnormal Volume.* All coefficients for comparability are statistically significant at 1 percent level except for Column (3), where the coefficient is marginally insignificant. Economically speaking, a one-standard-deviation increase in *Comparability SIC (TNIC)* is associated with an increase of 87.6 (67.04) thousand shares in the *Abnormal Volume*. This is consistent with the argument that comparability reduces information processing costs and encourages investors to process and trade on the new information in the earnings announcements, leading to a higher trading volume around earnings announcements.

6.3 Financial Statement Comparability and Short Seller

Short selling constitutes a significant portion of overall trading activity in the U.S. stock markets (Diether, Lee, and Werner 2019). Short sellers use their knowledge and skill advantage to arbitrage on price differentials (Boehmer, Jones, and Zhang 2008). Kim, Li, Lu, and Yu (2016) find that financial statement comparability disinclines managers from bad news hoarding, which reduces investors' perception of a firm's future crash risk. As sophisticated investors whose information advantage comes from their ability to process financial statement indicators that point to overvaluation (Beneish, Lee, and Nichols 2015), short sellers should be able to interpret the signal and target firms with low financial statements comparability. Following Desai, Krishnamurthy, and Venkataraman (2006), I use the measure of short interest to examine whether short sellers target firms with low financial statement comparability.

The results are presented in Table 9. Columns (1) and (2) present the result when I use the two input-based measures of financial statement comparability, respectively. As expected, there is a negative relation between comparability and short interest (statistically significant at 5% and 1%). The negative relation is also economically significant: one standard deviation increase in *Comparability SIC* (*Comparability TNIC*) is associated with a decrease of 2.4% (4.6%) in short interest. It seems that short sellers indeed avoid firms with high accounting comparability and target firms with low accounting comparability. Managers may be able to use financial statement comparability as a guard against the downward pressure on firms' stock prices from short sellers.

Next, I investigate whether short sellers influence the relation between financial statement comparability and price discovery. Although there is evidence that short sellers contribute to market efficiency (Engelberg, Reed, and Ringgenberg 2012), their unique payoff structure (profiting from a price decline) raises the concern that short sellers might manipulate the market through abusive trading or spreading false information (Purnanandam and Seyhun 2018). As a

result, the benefit of comparability on price discovery might be offset by the manipulative trading from short sellers. I run the following regression to test the conjecture:

$$Intraperiod\ Timeliness_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\ High\ Short\ Interest_{\ i,t} + \gamma_3\left(Comparability_{i,t} \times High\ Short\ Interes_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t} \quad (6)$$

where $High\ Short\ Interest_{\ i,t}$ is a dummy variable equal to 1 (0) if firm's short interest is in the top (bottom) tercile based on short interest in that quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects, respectively; $X_{i,t}$ is a vector of control variables as defined in Equation (5). The coefficient of interest is γ_3. As shown in columns (3) and (4), γ_3 is statistically insignificant in both specifications. It seems that financial statement comparability could influence short sellers' investment decisions. Meanwhile, although short sellers could influence the relation between comparability and price discovery systematically, I do not find evidence supporting the conjecture.

6.4 Financial Statement Comparability and Algorithmic Trader

Algorithmic trading has come to dominate stock, futures, and Treasury markets in the United States and globally (Weller 2018). Algorithmic traders use a computer program that follows a defined set of instructions (an algorithm) to place a trade. On the one hand, algorithmic traders may put more emphasis on hard information of the stock (such as moving average returns), timing, mathematical model while paying less attention to the financial statement comparability. On the other hand, a firm with high comparability may help the algorithmic traders to extract needed information more easily or develop models that have a wider range of application.

Following Weller (2018) and Lee and Watts (2021), I constructed four proxies for algorithmic trading using the data from the SEC Market Information Data Analytics System (MIDAS). After it was launched in January 2013, MIDAS provides microsecond stamped order

book information from all major U.S. exchanges. It incorporates quote and cancellation information from the entire order book. [14] The four proxies include the odd-lot ratio, trade-to-order ratio, cancel-to-trade ratio, and average trade size. The calculation of each proxy can be found in the Appendix. Algorithmic traders tend to make odd-lot trades (O'Hara, Yao, and Ye 2014) and are more likely to submit limit orders (Brogaard, Hendershott, and Riordan 2019). They can quickly replace their stale quotes with updated ones, which leads to a rapid chain of order submissions and cancellations. Also, algorithmic traders have the tendency to slice large, parent orders into a series of smaller, child orders. As a result, a higher level of algorithmic trading activity is associated with a higher odd lot ratio, a lower trade-to-order ratio, a higher cancel-to-trade ratio, and a smaller average trade size.

To check whether comparability influences the decisions of algorithmic traders, I regress the proxies for algorithmic trading on financial statement comparability. The results are presented in Table 10, Panel A. Out of the eight columns, only the Column for cancel-to-trade ratio shows a marginally significant negative coefficient. It seems that comparability does not influence algorithmic traders' trading decisions. One possible interpretation is that algorithmic traders indeed care more about stocks' hard information and mathematical model, etc.

Next, I examine whether algorithmic traders influence the relation between financial statement comparability and price discovery. I use Equation (5), replace $High\ Short\ Interest_{i,t}$ with $High\ Algorithmic\ Trading_{i,t}$, where $High\ Algorithmic\ Trading_{i,t}$ is equal to 1 (0) if the firm's proxy for algorithmic trading is in the top (bottom) tercile in that quarter. The results are presented in Table 10, Panel B. The coefficients of interaction terms in columns (2) and (4) are significant at the 5% level, indicating that the benefits of comparability on price discovery will

[14] Using this information, the SEC provides daily summary information to public on total volume, odd lot volume, and counts of trades and cancellations. The data is free to access at SEC.gov | Market Structure Data Downloads.

be stronger when the average trade size is bigger and when the trade-to-order ratio is higher. One possible explanation is that, by construct, the proxies for algorithmic trading are an inverse measure of the level of human traders. Therefore, the results indicate that when there are more human investors, who make more use of information in the financial statements compared with algorithmic traders, the benefits of comparability on price discovery will be stronger.[15] However, I need to interpret these results with caution, as the coefficients of the interaction terms are not consistently significant.

In sum, low financial statement comparability will attract short sellers but not algorithmic traders. The benefits of financial statement comparability in reducing information processing costs will be stronger for firms with a low level of algorithmic trading (high level of human trader). The level of short interest would not influence the positive relation between comparability and the speed of price discovery.

6.5 Controlling for Accrual Quality, Product Similarity, and Accounting Complexity

Next, I check the robustness of my results while controlling for firms' accrual quality, product similarity, and accounting complexity. Financial statement comparability is an enhancing characteristic of accounting information, which is distinct from the fundamental accounting characteristics such as representational faithfulness and relevance (FASB 2010). I use the measure of discretionary accruals, following Jones (1991) and Kothari, Leone, and Wasley (2005), as a proxy for fundamental within-firm accounting quality. Since accounting reports are intended to summarize the firms' economic activities, accounting comparability is distinct but inseparable from economic comparability. I use the product similarity measure from Hoberg and Phillips

[15] For the sake of space, I only report the results using two proxies for algorithmic trading. The results using the other two measures (odd lot ratio and cancel-to-trade ratio) are qualitatively similar.

(2016)[16], who analyzed the textual similarity in peer firms' business and product descriptions in 10-K filings. Another related quality of accounting information is the accounting reporting complexity, which is based on the count of the number of monetary XBRL tags in 10-K financial statements and notes (Hoitash and Hoitash 2018).[17] I add these three measures in Equation (3) as additional control variables. The results are presented in Table 11. The coefficients for comparability remain statistically significant when controlling for the three measures separately from Column (1) to Column (6) and when controlling for all three at the same time in Columns (7) and (8). [18] The results indicate that the comparability measure is distinct from measures of within-firm accounting quality, economic comparability, and accounting complexity.

6.6 Other Robustness Tests

I also perform a battery of untabulated sensitivity analyses. First, I rerun the baseline regressions with alternative fixed effect structures to ensure my findings are not limited to a particular fixed effect structure. In the main analyses, I include firm fixed effects and year-quarter fixed effects to absorb any time-invariant characteristics of firms and any factors specific to a quarter that may relate to their comparability and the stock price discovery process. In the sensitivity tests, I estimate the equations without any fixed effects, then replace the firm fixed effects and year-quarter fixed effects with industry fixed effects, year fixed effects, the product of industry, and year fixed effects. Second, I convert the comparability measures into ranked variables (decile, quartile) and repeat the analyses. Third, when examining the influence of comparability on price response and post-earnings-announcement drift, I use a full interaction model where the interaction terms between comparability and all control variables are included.

[16] Hoberg and Phillips' similarity data is available at Hoberg and Phillips Data Library (dartmouth.edu).
[17] The accounting complexity data is available at XBRL Research Data.
[18] The results remain similar if I use cumulative returns of various return windows as the dependent variable.

Lastly, I use the lagged value of the comparability score to run the analyses. Neither of the analyses changes my inference.

7. Conclusion

In this paper, I study how comparability affects the price discovery process. More specifically, using a new input-based measure of financial statement comparability and the setting of earnings announcements, I find that comparability is associated with stronger short-window price reactions to earnings news, higher Intraperiod timeliness, and smaller magnitude of post-earnings-announcement-drift. These results suggest that financial statement comparability reduces information processing costs and improves price discovery speed. Additionally, I find that the relation between comparability and price discovery is not influenced by the order in which the earnings are announced. Investors tend to search for more peer information before earnings announcements when focal firms have higher financial statement comparability. I also find that the relation between comparability and price discovery becomes stronger in more recent years. In addition, (abnormal) trading volume around earnings announcement is positively associated with comparability. I find that short interests are negatively associated with financial statement comparability and that algorithmic traders weaken the benefits of comparability on price discovery.

My study adds to the prior literature that examines the benefits of financial statement comparability. By using the input-based measure, which does not assume market efficiency, I provide direct evidence of the improvement in the speed of price discovery brought by financial statement comparability. The results of my study also have policy implications for standard setters and practical implications for managers regarding short sellers.

Reference

Anderberg, M., 1973. Cluster Analysis for Applications. New York, NY: Academic Press.

Ball, R., Bartov, L., 1996. How naive is the stock market's use of earnings information? *Journal of Accounting and Economics*, 21(3), 319-337.

Barth, M., Landsman, W., Lang, M., Williams, C., 2012. Are IFRS-based and US GAAP-based accounting amounts comparable? *Journal of Accounting and Economics*, 54 (1), 68–93.

Beaver, W., 1968. The information content of annual earnings announcements. *Journal of Accounting Research*, 6 (Selected Studies), 67-92.

Beneish, M.D., Lee, C.M.C., and Nichols D.C., 2015, In short supply: Short-sellers and stock returns, *Journal of Accounting and Economics* 60(2-3), 33- 57

Bentley, J., Christensen, T., Gee, K. and Whipple, B., 2018. Disentangling managers' and analysts' non-GAAP reporting. *Journal of Accounting Research*, 56(4), 1039-1081.

Bernard., V, Thomas, J., 1989. Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research*, 27, 1-36.

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), 1013-1044.

Blankespoor, E., deHaan, E., Zhu, C., 2018. Capital market effects of media synthesis and dissemination: Evidence from robo-journalism. *Review of Accounting Studies*, 23(1), 1-36.

Blankespoor, E., Miller, B., White, H., 2014. Initial evidence on the market impact of the XBRL mandate. *Review of Accounting Studies*, 19(4), 1468-1503.

Boehmer, E., Jones, C., Zhang, X., 2008. Which shorts are informed? *The Journal of Finance*, 63(2), 491-527.

Brochet, F., Jagolinzer, A., Riedl, E., 2013. Mandatory IFRS adoption and financial statement comparability. *Contemporary Accounting Research*, 30(4), 1373–1400.

Brogaard, J., Hendershott, T., Riordan, R., 2019. Price discovery without trading: Evidence from limit orders. *The Journal of Finance*, 74(4), 1621-1658.

Bushman, R., Smith, A., Wittenberg-Moerman, R., 2010. Price discovery and dissemination of private information by loan syndicate participants. *Journal of Accounting Research*, 48(5), 921-972.

Butler, M., Kraft, A., Weiss, I., 2007. The effect of reporting frequency on the timeliness of earnings: The cases of voluntary and mandatory interim reports. *Journal of Accounting and Economics*, 43(2-3), 181-217.

Chen, C., Collins, D., Kravet, T., Mergenthaler, R., 2018. Financial statement comparability and the efficiency of acquisition decisions. *Contemporary Accounting Research*, 35(1),164-202.

Chircop, J., Collins, D., Hass, L., Nguyen, N., 2020. Accounting comparability and corporate innovative efficiency. *The Accounting Review*, 95(4), 127-151.

DeFond, M., Hu, X., Hung, M., Li, S., 2011. The impact of mandatory IFRS adoption on foreign mutual fund ownership: The role of comparability. *Journal of Accounting and Economics*, 51 (3), 240–258

De Franco, G., Kothari, S.P., Verdi, R., 2011. The benefits of financial statement comparability. *Journal of Accounting Research*, 49(4), 895-931.

deHaan, E., Shevlin, T., Thornock, J., 2015. Market (in)attention and the strategic scheduling and timing of earnings announcements. *Journal of Accounting and Economics*, 60(1), 36-55.

Desai, H., Krishnamurthy, S., Venkataraman, K., 2006. Do short sellers target firms with poor earnings quality? Evidence from earnings restatements. *Review of Accounting Studies*, 11(1), 71-90.

Diether, K., Lee, K., Werner, I., 2009. It's SHO time! Short-sale price tests and market quality. *Journal of Finance*, 64(1), 37-73.

Dye, R. & Sunder, S. (2001). Why not allow FASB and IASB standards to compete in the U.S.? *Accounting Horizons*, 15, 257–271

Engelberg, J., Reed, A., Ringgenberg, M., 2012. How are shorts informed? Short sellers, news, and information processing. *Journal of Financial Economics*, 105(2), 260-278.

Financial Accounting Standard Board, 2010. Statement of Financial Accounting Concepts no.8. Available at: (https://www.fasb.org/jsp/FASB/Document_C/DocumentPage?cid=1176157498129)

Francis, J., Pinnuck, M., Watanabe, O., 2014. Auditor style and financial statement comparability. *The Accounting Review*, 89(2), 605–633.

Goldstein, I., Yang, S., and Zuo, L., 2022. The real effects of modern information technologies: Evidence from the EDGAR implementation. Working paper.

Grossman, S., and Stiglitz, J., 1980. On the impossibility of informationally efficient markets. *American Economic Review*. 70(3), 393–408.

Guest, N., 2021. The information role of the media in earnings news. *Journal of Accounting Research*, 59(3), 1021-1076

Hirshleifer, D., Teoh, S., 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics*, 36(1-3), 337-386.

Hoberg, G., Phillips, G., 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124 (5), 1423–1465.

Hoitash, R.,and Hoitash, U., 2018. Measuring accounting reporting complexity with XBRL. *The Accounting Review*, 93(1), 259-287.

Hoitash, R., Hoitash, U., Kurt, A., Verdi, R., 2018. An input-based measure of financial statement comparability. Working paper.

Imhof, M., Seavey, S., Smith, D., 2017. Comparability and cost of equity capital. *Accounting Horizons*, 31(2), 125-138.

Imhof, M., Seavey, S., and Watanabe, O., 2018. Competition, proprietary costs of financial reporting, and financial statement comparability. *Journal of Accounting, Auditing & Finance*.

Jones, J., 1991. Earnings management during import relief investigations. *Journal of Accounting Research*, 29(2), 193–228.

Karpoff, J., 1986. A theory of trading volume. *The Journal of Finance*, 41(5), 1069-1087.

Kvaal, E., Nobes, C., 2012. IFRS policy changes and the continuation of national patterns of IFRS practice. *European Accounting Review*, 21(2), 343–71.

Kim, S., Kraft, P., Ryan, S., 2013. Financial statement comparability and credit risk. *Review of Accounting Studies*, 18(3), 783-823.

Kim, J., Li, L., Lu, L., Yu, Y., 2016. Financial statement comparability and expected crash risk. *Journal of Accounting and Economics*, 61(2-3), 294-312.

Kim, O., Verrecchia, R., 1991. Trading volume and price reactions to public announcements. *Journal of Accounting Research*, 29(2), 302-321.

Kim, O., Verrecchia, R., 1994. Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics*, 17(1-2), 41-67.

Kothari, S. P., Leone, A., and Wasley, C., 2005. Performance matched discretionary accruals measures. *Journal of Accounting and Economics*, 39 (1), 163–197.

Lee, C., Ma, P., and Wang., C., 2015. Search-based peer firms: Aggregating investor perceptions through internet co-searches. *Journal of Financial Economics*, 116(2), 410–431.

Lee, C., Watts, E., Tick size tolls: Can a trading slowdown improve earnings news discovery? *The Accounting Review*, 96(3), 373-401.

Livnat, J., Mendenhall, R., 2006. Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research*, 44(1), 177-205.

Noh, S., So, E. and Verdi, R., 2021. Calendar rotations: A new approach for studying the impact of timing using earnings announcements. *Journal of Financial Economics*, 140(3), 865-893.

O'Hara, M., Yao, C., Ye M., 2014. What's not there: Odd lots and market data. *The Journal of Finance*, 69(5), 2199-2236.

Purnanandam, A., Seyhun, H., 2018. Do short sellers trade on private information or false information? *Journal of Financial and Quantitative Analysis*, 53(3), 997-1023.

Ryans, J., 2017. Using the EDGAR log file data set. Working paper.

Twedt, B., 2016. Spreading the word: Price discovery and newswire dissemination of management earnings guidance. *The Accounting Review*, 91(1), 317-346

Weller, B., 2018. Does algorithmic trading reduce information acquisition? *The Review of Financial Studies*, 31(6), 2184–2226.

Yip, R., Young, D., 2012. Does mandatory IFRS adoption improve information comparability? *The Accounting Review*, 87(5), 1767-1789.

Young, S., Zeng., 2015. Accounting comparability and the accuracy of peer-based valuation models. *The Accounting Review*, 90 (6), 2571–2601.

Zhang, J., 2018. Accounting comparability, audit effort, and audit outcomes. *Contemporary Accounting Research*, 35 (1), 245-276

Appendix: Variable Definitions	
Accounting Complexity	The natural log of the total number of distinct monetary XBRL tags in Item 8 of the 10-K flings.
Abnormal Vol	$Vol^{[-1,1]} - Vol^{[-22,-2]}$, where $Vol^{[-1,1]}$ is the average daily trading volume around earnings announcements, and $Vol^{[-22,-2]}$ is the average daily trading volume from day -22 to day -2.
Asset Growth	Total assets divided by lagged total assets, minus 1.
Average Trade Size	$Average\ Trade\ Size_{i,t} = \frac{Total\ Trade\ Volume_{i,t}}{Count\ of\ Trades_{i,t}}$ where $Total\ Trade\ Volume_{i,t}$ is the the sum of all trade volume and $Count\ of\ Trades_{i,t}$ is the count of all trades for all 12 stock exchanges captured by the SEC MIDAS system excluding the NYSE and AMEX due to data comparability issues with other exchanges.
Book-to-market	Book to market: calculated as Compustat CEQQ divided by market value.
$CAR_{i,t}^{[a,b]}$	Cumulative abnormal stock return for a firm from day a through day b relative to the quarterly earnings announcement. Computed as firm's raw return minus the value-weighted return for a portfolio of firms matched on 5×5 sorts of firm size and market-to-book ratio.
Cancel-to-Trade Ratio	$Cancel\ to\ Trade\ Ratio_{i,t} = \frac{Count\ of\ Cancels_{i,t}}{Count\ of\ Trades_{i,t}}$ where $Count\ of\ Cancels_{i,t}$ is the count of all canceled orders and $Count\ of\ Trades_{i,t}$ is the count of all trades for all 12 stock exchanges captured by the SEC MIDAS system excluding the NYSE and AMEX due to data comparability issues with other exchanges.
Comparability SIC	The measure of financial statement comparability following the approach by Hoitash, Hoitash, Kurt, and Verdi (2018) based on SIC industry classification.
Comparability TNIC	The measure of financial statement comparability following the approach by Hoitash, Hoitash, Kurt, and Verdi (2018) based on textual-based network industry classification.
Days to Cover	Short interest divided by average daily share volume.
Discretionary Accruals	Discretionary accruals following Kothari, Leone, and Wasley (2005). $TA_{i,t} = \beta_0 + \beta_1 \times \frac{1}{Assets_{i,t-1}} + \beta_2 \times \Delta Sales_{i,t} + \beta_3 \times PPE_{i,t} + \varepsilon_{i,t}$ Total accruals (TA) is the change in non-cash current assets minus the change in current liabilities excluding the current portion of long-term debt, minus depreciation and amortization, scaled by lagged total assets. The Jones model discretionary accrual is estimated cross-sectionally each year using all firm-year observations in the same two-digit SIC code. I use residuals from the annual cross-sectional industry regression model as the Jones model discretionary accruals.
EA Order	The ratio of n over N, where N is the number of firms with the same fiscal period end within the same SIC industry, and n is the ranking of a given firm's earnings announcement timing among N firms.
Early	Dummy variable equal to 1 if the observation is before 2005, 0 otherwise.
$ESV_{i,t}^{[T_0,T_1]}$	$ESV_{i,t}^{[T_0,T_1]} = \sum_{k=T_0}^{T_1} ESV_{i,t}^{k}$ where $ESV_{i,t}^{k}$ is that total non-robotic EDGAR downloads across all disclosures for each day k relative to the earnings date.
Institutional Ownership	Fraction of shares held by institutional investors, calculated at the most recent file date between 100 days before the earnings announcement date and the earnings announcement date.
Intraperiod Timeliness	$IPT_{i,t} = \sum_{j=0}^{5} \frac{CAR_{i,t}^{[0,j]}}{CAR_{i,t}^{[0,5]}} + 0.5$
Loss	Dummy variable equal to 1 if EPS is negative.
No. of Analysts	Log of 1 plus the number of IBES analysts following the firm.

Odd Lot Ratio	$Odd\ Lot\ Ratio_{i,t} = \frac{Odd\ Lot\ Volum_{i,t}}{Total\ Trade\ Volume_{i,t}}$ where $Odd\ Lot\ Volum_{i,t}$ is the sum of all odd lot trade volume and $Total\ Trade\ Volume_{i,t}$ is the sum of all trade volume for all 12 stock exchanges captured by the SEC MIDAS system, excluding the NYSE and AMEX due to data comparability issues with other exchanges.
Output-based Comparability	Financial statement comparability measure constructed using the approach of De Franco, Kothari, and Verdi (2011).
$Peer\_ESV_{i,t}^{[T_0,T_1]}$	Total non-robotic EDGAR downloads across all disclosures from T_0 to T_1 for most comparable firms within the industry, based on the pairwise comparability score.
Product Similarity	Product similarity measure from Hoberg and Phillips (2016), who analyzed the textual similarity in peer firms' business and product descriptions in 10-K filings, available at Hoberg and Phillips Data Library (dartmouth.edu)
ROA	Return on assets, calculated as net income divided by total assets.
Short Interest	Shares held as short position over total number of shares outstanding, available from Compustat.
Size	Logarithm of market capitalization.
SUE	Standardized Decile ranking (0 = low, 1= high, by year-quarter) of unexpected earnings (UE). UE is defined as the mean of IBES UE. IBES UE is the difference between actual EPS and consensus EPS reported by IBES, scaled by the quarter-end CRSP price (adjusted for stock splits). If IBES UE is not available, this variable is the decile ranking of seasonal random walk UE, calculated as the difference between current quarter EPSFXQ and one-year-prior EPSFXQ, scaled by the one-year-prior quarter-end CRSP price (adjusted for stock splits).
Trade-to-Order Ratio	$Trade\ to\ Order_{i,t} = \frac{Total\ Trade\ Volume_{i,t}}{Total\ Order\ Volume_{i,t}}$ where $Total\ Trade\ Volume_{i,t}$ is the sum of all trade volume and $Total\ Order\ Volume_{i,t}$ is the sum of all order volume for all 12 stock exchanges captured by the SEC MIDAS system, excluding the NYSE and AMEX due to data comparability issues with other exchanges.

Table 1. Sample Summary Statistics

This table reports summary statistics for the main variables used in my empirical analyses. Variables are defined in Appendix 1. All variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers.

Variable	Mean	St. Dev.	25th Pct.	Median	75th Pct.	Obs.
Comparability SIC	0.65	0.04	0.62	0.65	0.67	71,962
Comparability TNIC	0.63	0.04	0.61	0.63	0.65	72,468
$CAR^{[0,1]}$*(%)*	0.11	9.23	-4.89	-0.01	5.26	73,435
$CAR^{[2,15]}$*(%)*	0.16	10.47	-5.22	-0.03	5.26	73,435
Intraperiod Timeliness	3.92	2.60	2.70	3.98	5.16	72,468
$Peer\_ESV^{[-10,1]}$	2.46	2.44	1.09	1.83	2.96	53,243
$Peer\_ESV^{[-1,1]}$	0.53	0.54	0.22	0.38	0.65	53,350
SUE	0.49	0.26	0.22	0.44	0.67	72,468
Size	4185.44	13142.20	241.43	723.69	2476.84	72,468
Book-to-Market	0.51	0.42	0.25	0.42	0.65	72,468
ROA	0.10	0.24	0.06	0.13	0.20	72,468
Institutional Ownership	0.65	0.26	0.46	0.68	0.85	72,468
No. of Analysts	5.42	5.16	2.00	4.00	7.00	72,468
Asset Growth	0.03	0.12	-0.02	0.01	0.05	72,468
Discretionary Accruals	-0.35	1.21	-0.25	-0.09	-0.03	70,508
Loss	0.27	0.44	0.00	0.00	1.00	72,468
Short Interest	0.05	0.05	0.02	0.03	0.07	56,690

Table 2. Financial Statement Comparability and Price Response to Earnings News

This table reports the effect of comparability on immediate market response to earnings news using the following regression specification:

$$CAR_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\, SUE_{\ i,t} + \gamma_3\left(Comparability_{i,t} \times SUE_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t}$$

where i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable					
	$CAR^{[0,1]}$		$CAR^{[0,2]}$		$CAR^{[0,3]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Comparability SIC	0.017		0.026		0.022	
	(0.020)		(0.022)		(0.024)	
Comparability TNIC		-0.001		0.012		0.006
		(0.017)		(0.019)		(0.020)
Comparability SIC×SUE	0.332***		0.340***		0.299***	
	(0.055)		(0.056)		(0.059)	
Comparability TNIC×SUE		0.415***		0.431***		0.404***
		(0.043)		(0.045)		(0.049)
SUE	-0.089**	-0.148***	-0.087**	-0.151***	-0.057	-0.129***
	(0.034)	(0.027)	(0.035)	(0.029)	(0.037)	(0.032)
Size	-0.013***	-0.013***	-0.015***	-0.015***	-0.018***	-0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Book-to-Market	0.001	0.001	0.009***	0.009***	0.004***	0.004***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
ROA	0.048***	0.048***	0.051***	0.051***	0.050***	0.051***
	(0.014)	(0.014)	(0.015)	(0.015)	(0.016)	(0.016)
Institutional Ownership	-0.000	-0.001	0.003	0.003	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
No. of Analysts	0.003***	0.003***	0.003***	0.003***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Asset Growth	0.008**	0.008**	0.008**	0.009**	0.007	0.008*

	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Loss	-0.007***	-0.007***	-0.008***	-0.008***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Constant	0.063***	0.074***	0.068***	0.077***	0.103***	0.112***
	(0.018)	(0.017)	(0.020)	(0.018)	(0.021)	(0.019)
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,468	71,962	72,468	71,962	72,468	71,962
Adjusted R-squared	0.134	0.135	0.134	0.135	0.129	0.129

Table 3. Financial Statement Comparability and Intraperiod Timeliness

This table reports the relation between Intraperiod Timeliness and comparability using the following regression specification:

$$Intraperiod\ Timeliness_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\ SUE_{\ i,t} + \beta X_{i,t} + \varepsilon_{i,t}$$

where i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable			
	Intraperiod Timeliness			
	(1)	(2)	(3)	(4)
Comparability SIC	1.500***	2.385***		
	(0.404)	(0.619)		
Comparability TNIC			1.102***	1.257**
			(0.338)	(0.521)
SUE		0.021		0.025
		(0.044)		(0.044)
Size		0.078***		0.079***
		(0.027)		(0.026)
Book-to-Market		0.017		0.011
		(0.027)		(0.027)
ROA		0.264		0.183
		(0.420)		(0.420)
Institutional Ownership		0.210**		0.198**
		(0.101)		(0.101)
No. of Analysts		0.012		0.015
		(0.025)		(0.025)
Asset Growth		0.003		-0.011
		(0.106)		(0.106)
Loss		-0.085**		-0.089**
		(0.039)		(0.039)
Friday		0.089*		0.081

		(0.054)		(0.055)
Constant	2.368***	0.415	2.607***	1.096**
	(0.329)	(0.574)	(0.303)	(0.539)
Year-Quarter FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Observations	163,241	72,468	162,023	71,962
Adjusted R-squared	0.027	0.037	0.028	0.037

Table 4. Financial Statement Comparability and Post-Earnings-Announcement Drift

This table reports the effect of comparability on post-earnings-announcement drift using the following regression specification:

$$CAR_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\, SUE_{\ i,t} + \gamma_3\left(Comparability_{i,t} \times SUE_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t}$$

where i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable					
	$CAR^{[2,10]}$		$CAR^{[2,15]}$		$CAR^{[2,20]}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Comparability SIC	0.013		0.012		0.015	
	(0.020)		(0.025)		(0.028)	
Comparability TNIC		0.011		0.015		0.030
		(0.017)		(0.021)		(0.024)
Comparability SIC×SUE	-0.146***		-0.201***		-0.212***	
	(0.042)		(0.051)		(0.058)	
Comparability TNIC×SUE		-0.119***		-0.178***		-0.178***
		(0.037)		(0.046)		(0.052)
SUE	0.112***	0.097***	0.150***	0.138***	0.158***	0.140***
	(0.026)	(0.024)	(0.032)	(0.030)	(0.037)	(0.034)
Size	-0.012***	-0.012***	-0.017***	-0.017***	-0.022***	-0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Book-to-Market	0.006***	0.006***	0.006***	0.006***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
ROA	0.028*	0.029*	0.045**	0.046**	0.060***	0.061***
	(0.017)	(0.017)	(0.021)	(0.021)	(0.023)	(0.023)
Institutional Ownership	0.003	0.003	-0.001	-0.001	-0.005	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
No. of Analysts	0.003***	0.003***	0.003***	0.003***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Asset Growth	-0.003	-0.003	-0.005	-0.005	-0.003	-0.003
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Loss	-0.003**	-0.003**	-0.004**	-0.004**	-0.005**	-0.004**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.097***	0.099***	0.136***	0.134***	0.166***	0.157***
	(0.019)	(0.018)	(0.023)	(0.021)	(0.026)	(0.024)
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,468	71,962	72,468	71,962	72,468	71,962
Adjusted R-squared	0.048	0.049	0.047	0.047	0.047	0.047

Table 5. The Influence of the Relative Orders of Earnings Announcement

This table reports the influence of the relative orders of earnings announcements on the relation between *Comparability* and the speed of price discovery using following regression specifications:

$$CAR_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\, SUE_{\ i,t} + \gamma_3\, EA\ Order_{\ i,t} + \gamma_4\left(Comparability_{i,t} \times SUE_{i,t} \times\ EA\ Order_{i,t}\right)$$
$$+ \gamma_5\left(Comparability_{i,t} \times\ EA\ Order_{i,t}\right) + \gamma_6\left(Comparability_{i,t} \times SUE_{i,t}\right) + \gamma_7\left(SUE_{i,t} \times\ EA\ Order_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t}$$

$$Intraperiod\ Timeliness_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2 EA\ Order_{\ i,t} + \gamma_3\left(Comprability_{i,t} \times\ EA\ Order_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t}$$

where i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable					
	$CAR^{[0,2]}$		$CAR^{[2,20]}$		*Intraperiod Timeliness*	
	(1)	(2)	(3)	(4)	(5)	(6)
Comparability SIC	0.048*		-0.006		2.406***	
	(0.026)		(0.031)		(0.620)	
Comparability TNIC		0.001		-0.011		1.283**
		(0.026)		(0.028)		(0.522)
EA Order	0.022*	-0.012	-0.016	-0.027	0.022	0.024
	(0.013)	(0.019)	(0.017)	(0.020)	(0.020)	(0.020)
SUE	-0.243***	-0.203***	0.139**	0.151***	0.022	0.026
	(0.055)	(0.056)	(0.063)	(0.057)	(0.044)	(0.044)
Comparability SIC×EA Order	-0.044**		0.027		-0.034	
	(0.021)		(0.027)		(0.081)	
Comparability TNIC×EA Order		0.012		0.043		-0.041
		(0.030)		(0.031)		(0.079)
Comparability SIC×EA Order×SUE	-0.427***		0.004			
	(0.103)		(0.127)			
Comparability TNIC×EA Order×SUE		-0.178		0.057		
		(0.119)		(0.116)		
Size	-0.016***	-0.016***	-0.017***	-0.017***	0.078***	0.079***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.027)	(0.026)
Book-to-Market	0.003**	0.003**	0.006***	0.006***	0.017	0.011
	(0.001)	(0.001)	(0.001)	(0.001)	(0.027)	(0.027)

ROA	0.046***	0.046***	0.046**	0.046**	0.264	0.183
	(0.015)	(0.015)	(0.021)	(0.021)	(0.420)	(0.420)
Institutional Ownership	0.003	0.003	-0.001	-0.001	0.189*	0.177*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.101)	(0.101)
No. of Analysts	0.003***	0.003***	0.003***	0.003***	0.012	0.015
	(0.001)	(0.001)	(0.001)	(0.001)	(0.025)	(0.025)
Asset Growth	0.008*	0.008*	-0.005	-0.005	0.002	-0.011
	(0.004)	(0.004)	(0.005)	(0.005)	(0.106)	(0.107)
Loss	-0.007***	-0.008***	-0.004**	-0.003**	-0.085**	-0.089**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.039)	(0.039)
Constant	0.072***	0.101***	0.147***	0.151***	0.399	1.081**
	(0.022)	(0.022)	(0.025)	(0.025)	(0.575)	(0.540)
Other Interaction Terms	Yes	Yes	Yes	Yes	No	No
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,478	71,972	72,478	71,972	72,478	71,972
Adjusted R-squared	0.133	0.133	0.047	0.047	0.037	0.037

Table 6. Financial Statement Comparability and Fundamental Information Acquisition

This table reports the relation between fundamental information acquisition and comparability using the following regression specification:

$$Y_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\ SUE_{\ i,t} + \beta X_{i,t} + \varepsilon_{i,t}$$

where $Y_{i,t}$ is the proxy for the acquisition of fundamental information activities; i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable							
	$Peer\_ESV^{[-10,1]}$	$Peer\_ESV^{[-1,1]}$	$Peer\_ESV^{[-10,1]}$	$Peer\_ESV^{[-1,1]}$	$ESV^{[-10,1]}$	$ESV^{[-1,1]}$	$ESV^{[-10,1]}$	$ESV^{[-1,1]}$
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Comparability SIC	5.222***	1.270***			0.025	0.037		
	(1.850)	(0.419)			(0.197)	(0.053)		
Comparability TNIC			2.426**	0.456*			0.020	0.035
			(1.222)	(0.265)			(0.124)	(0.035)
Size	0.006	-0.001	0.012	0.001	0.003	-0.000	0.003	-0.000
	(0.040)	(0.010)	(0.040)	(0.010)	(0.004)	(0.002)	(0.004)	(0.002)
Book-to-Market	0.187**	0.037*	0.197**	0.040*	0.064	0.018	0.064	0.018
	(0.087)	(0.020)	(0.087)	(0.021)	(0.039)	(0.011)	(0.040)	(0.011)
ROA	0.075	0.012	0.068	0.011	0.027	0.007	0.026	0.007
	(0.066)	(0.017)	(0.065)	(0.017)	(0.019)	(0.005)	(0.019)	(0.005)
Institutional Ownership	0.006	-0.026	0.071	-0.009	-0.062*	-0.014	-0.061*	-0.014
	(0.240)	(0.060)	(0.240)	(0.060)	(0.035)	(0.011)	(0.035)	(0.012)
No. of Analysts	0.000***	0.000***	0.000***	0.000***	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Asset Growth	0.007	0.011	0.004	0.010	0.016***	0.005***	0.015***	0.005***
	(0.032)	(0.007)	(0.032)	(0.007)	(0.004)	(0.001)	(0.004)	(0.001)
Loss	0.026	-0.006	0.019	-0.009	-0.015	-0.001	-0.014	-0.000
	(0.088)	(0.022)	(0.088)	(0.022)	(0.021)	(0.005)	(0.021)	(0.005)
Constant	-0.100***	-0.018**	-0.102***	-0.019**	0.020**	0.006**	0.020**	0.006**
	(0.032)	(0.008)	(0.032)	(0.008)	(0.009)	(0.003)	(0.009)	(0.003)

Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,161	31,198	30,917	30,953	44,819	44,878	44,489	44,547
Adjusted R-squared	0.556	0.529	0.556	0.529	0.591	0.611	0.588	0.608

Table 7. Time-Series Change of the Relation between Comparability and Price Discovery

This table reports the time-series change of the relation between *Comparability* and the speed of price discovery using following regression specifications:

$$CAR_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\, SUE_{\ i,t} + \gamma_3\, Early_{\ i,t} + \gamma_4\left(Comparability_{i,t} \times SUE_{i,t} \times\ Early_{i,t}\right) + \gamma_5\left(Comparability_{i,t} \times\ Early_{i,t}\right) + \gamma_6\left(Comparability_{i,t} \times SUE_{i,t}\right) + \gamma_7\left(SUE_{i,t} \times\ Early_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t}$$

$$Intraperiod\ Timeliness_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2 Early_{\ i,t} + \gamma_3\left(Comprability_{i,t} \times\ Early_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t}$$

where i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; *Early* is a dummy variable equal to 1 X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable					
	$CAR^{[0,2]}$		$CAR^{[2,60]}$		Intraperiod Timeliness	
	(1)	(2)	(3)	(4)	(5)	(6)
Comparability SIC	0.035		0.140**		2.300***	
	(0.025)		(0.059)		(0.713)	
Comparability TNIC		-0.006		0.116**		1.824***
		(0.021)		(0.049)		(0.571)
SUE	-0.173***	-0.186***	0.247**	0.322***	0.020	0.025
	(0.049)	(0.038)	(0.099)	(0.083)	(0.044)	(0.044)
Early	-0.005	-0.043**	0.025	-0.002	-1.629**	-0.682
	(0.022)	(0.020)	(0.049)	(0.047)	(0.658)	(0.603)
Comparability SIC×Early	-0.030		-0.045		0.169	
	(0.027)		(0.060)		(0.781)	
Comparability TNIC×Early		0.029		-0.004		-1.334**
		(0.023)		(0.054)		(0.651)
Comparability SIC×SUE×Early	-0.371***		0.643***			
	(0.109)		(0.237)			
Comparability TNIC×SUE×Early		-0.253***		0.440**		
		(0.087)		(0.212)		
Size	-0.016***	-0.016***	-0.066***	-0.067***	0.078***	0.083***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.027)	(0.026)
Book-to-Market	0.002**	0.002**	-0.014***	-0.014***	0.016	0.014
	(0.001)	(0.001)	(0.003)	(0.003)	(0.027)	(0.027)
ROA	0.046***	0.046***	-0.092**	-0.097**	0.265	0.181

	(0.015)	(0.015)	(0.045)	(0.045)	(0.419)	(0.419)
Institutional Ownership	0.002	0.003	-0.050***	-0.049***	0.187*	0.167
	(0.004)	(0.004)	(0.010)	(0.010)	(0.102)	(0.101)
No. of Analysts	0.003***	0.003***	0.002	0.003	0.011	0.015
	(0.001)	(0.001)	(0.002)	(0.002)	(0.025)	(0.025)
Asset Growth	0.007*	0.008*	-0.002	-0.001	0.002	-0.013
	(0.004)	(0.004)	(0.011)	(0.011)	(0.106)	(0.106)
Loss	-0.008***	-0.008***	0.003	0.003	-0.084**	-0.089**
	(0.001)	(0.001)	(0.004)	(0.004)	(0.039)	(0.039)
Constant	0.072***	0.101***	0.147***	0.151***	0.399	1.081**
	(0.022)	(0.022)	(0.025)	(0.025)	(0.575)	(0.540)
Other Interaction Terms	Yes	Yes	Yes	Yes	No	No
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,478	71,972	72,478	71,972	72,478	71,972
Adjusted R-squared	0.133	0.134	0.047	0.047	0.037	0.037

Table 8. Financial Statement Comparability and Trading Volume

This table reports the relation between *(Abnormal) Trading Volume* and comparability using the following regression specification:

$$Y_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\, SUE_{\ i,t} + \beta X_{i,t} + \varepsilon_{i,t}$$

where Y can be $Vol^{[-1,1]}$ or *Abnormal Vol*; i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable			
	$Vol^{[-1,1]}$		*Abnormal Vol*	
	(1)	(2)	(3)	(4)
Comparability SIC	4.143***		2.190***	
	(1.461)		(0.638)	
Comparability TNIC		2.276		1.676***
		(1.414)		(0.625)
SUE	-0.024	-0.023	-0.050**	-0.050**
	(0.044)	(0.043)	(0.025)	(0.025)
Size	0.696***	0.672***	0.261***	0.253***
	(0.112)	(0.108)	(0.049)	(0.048)
Book-to-Market	0.324***	0.309***	0.111**	0.105**
	(0.111)	(0.111)	(0.054)	(0.054)
ROA	0.483	0.445	0.691***	0.670***
	(0.388)	(0.389)	(0.207)	(0.207)
Institutional Ownership	-1.342***	-1.340***	-0.338**	-0.342**
	(0.319)	(0.318)	(0.137)	(0.137)
No. of Analysts	0.160***	0.162***	0.033*	0.033*
	(0.035)	(0.035)	(0.017)	(0.017)
Asset Growth	-0.058	-0.043	-0.027	-0.027
	(0.091)	(0.088)	(0.057)	(0.056)
Loss	0.072	0.056	-0.027	-0.032
	(0.049)	(0.049)	(0.024)	(0.024)
Constant	-6.024***	-4.741***	-2.770***	-2.414***
	(1.125)	(1.140)	(0.489)	(0.498)
Year-Quarter FEs	Yes	Yes	Yes	Yes

Firm FEs	Yes	Yes	Yes	Yes
Observations	72,468	71,962	72,468	71,962
Adjusted R-squared	0.721	0.723	0.548	0.549

Table 9. Financial Statement Comparability and Short Selling

This table reports the relation between short selling and comparability.
For Columns (1) and (2), I use the following regression specification:

$$Short\ Interests_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2\ SUE_{\ i,t} + \beta X_{i,t} + \varepsilon_{i,t}$$

For Columns (3) and (4), I use the following regression specification:

$$Intraperiod\ Timeliness_{i,t} = \alpha_t + \eta_i + \gamma_1 FSC_{i,t} + \gamma_2\ Short\ Interests_{\ i,t} + \gamma_3\left(FSC_{i,t} \times Short\ Interests_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t}$$

where i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss (for Column (1) and (2), additional control variables are added, including Leverage, Days-to-Cover, Average Trading Volume); ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable:			
	Short Interests		Intraperiod Timeliness	
	(1)	(2)	(3)	(4)
Comparability SIC	-0.030**		1.572*	
	(0.014)		(0.923)	
Comparability TNIC		-0.058***		1.831**
		(0.013)		(0.917)
High Short Interest			-0.862	0.244
			(0.663)	(0.630)
Comparability×High Short Interest			1.070	-0.189
			(0.959)	(0.967)
Size	-0.010***	-0.010***	0.045	0.050
	(0.001)	(0.001)	(0.034)	(0.034)
Book-to-Market	-0.007***	-0.007***	-0.012	-0.018
	(0.001)	(0.001)	(0.058)	(0.058)
ROA	-0.001	-0.002	-0.057	-0.070
	(0.004)	(0.004)	(0.503)	(0.504)
Institutional Ownership	0.066***	0.066***	0.185	0.162
	(0.003)	(0.003)	(0.134)	(0.134)
No. of Analysts	0.020***	0.020***	-0.017	-0.014
	(0.001)	(0.001)	(0.033)	(0.033)

Asset Growth	0.024***	0.024***	-0.006	-0.027
	(0.001)	(0.001)	(0.130)	(0.130)
Loss	0.006***	0.006***	-0.095*	-0.092*
	(0.001)	(0.001)	(0.049)	(0.049)
Leverage	-0.000**	-0.000**		
	(0.000)	(0.000)		
Days to Cover	0.006***	0.006***		
	(0.000)	(0.000)		
Average Trading Volume	0.000***	0.000***		
	(0.000)	(0.000)		
Constant	-0.006	0.012	1.345*	0.928
	(0.013)	(0.013)	1.345*	0.928
Year-Quarter FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Observations	21,007	20,828	47,363	47,033
Adjusted R-squared	0.536	0.537	0.035	0.034

Table 10. Financial Statement Comparability and Algorithmic Trading

Panel A:

This table reports the relation between algorithmic trading and comparability using the following regression specification:

$$Y_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \beta X_{i,t} + \varepsilon_{i,t}$$

where $Y_{i,t}$ is the proxy for the algorithmic trading activities; i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable:							
	Odd Lot Ratio		Trade-to-Order Ratio		Cancel-to-Trade Ratio		Average Trade Size	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Comparability SIC	-4.173		-0.533		-47.953		37.009	
	(6.000)		(2.101)		(30.310)		(31.669)	
Comparability TNIC		-3.338		1.490		-27.047*		-20.996
		(3.497)		(1.773)		(14.026)		(32.938)
Size	3.062***	3.039***	0.051	0.052	-0.888	-0.913	-23.146***	-22.738***
	(0.227)	(0.228)	(0.154)	(0.156)	(1.218)	(1.223)	(2.652)	(2.660)
Book-to-Market	0.084	0.062	0.063	0.068	1.853	1.891	0.479	0.424
	(0.180)	(0.182)	(0.128)	(0.130)	(1.156)	(1.175)	(1.892)	(1.919)
ROA	-1.891	-1.769	2.266*	2.240*	-12.071	-12.285	17.063	15.264
	(1.820)	(1.825)	(1.297)	(1.298)	(16.035)	(16.137)	(20.042)	(20.126)
Institutional Ownership	-2.475***	-2.410**	1.224**	1.156**	-8.965	-8.846	-10.315	-10.830
	(0.950)	(0.953)	(0.546)	(0.548)	(6.249)	(6.279)	(8.381)	(8.441)
No. of Analysts	-0.208**	-0.205**	0.023	0.025	-0.605	-0.603	0.881	0.940
	(0.103)	(0.104)	(0.058)	(0.058)	(0.576)	(0.580)	(0.812)	(0.812)
Asset Growth	-0.920**	-0.877**	-0.019	-0.019	-5.739**	-5.457**	0.427	-0.548
	(0.383)	(0.382)	(0.279)	(0.281)	(2.759)	(2.761)	(3.342)	(3.296)
Loss	0.062	0.076	-0.019	-0.025	0.725	0.788	-1.522	-1.778
	(0.172)	(0.174)	(0.102)	(0.102)	(1.083)	(1.105)	(1.605)	(1.620)
Constant	-6.689*	-6.960**	-0.535	-1.768	63.526***	51.886***	253.409***	286.449***
	(3.919)	(2.714)	(1.566)	(1.496)	(18.853)	(11.426)	(27.379)	(30.199)
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Observations	8,271	8,196	8,271	8,196	8,271	8,196	8,271	8,196
Adjusted R-squared	0.716	0.717	0.612	0.612	0.424	0.423	0.784	0.784

Table 10. Financial Statement Comparability and Algorithmic Trading

Panel B:

This table reports the mitigating effect of algorithmic trading using the following regression specification:

$$Intraperiod\ Timeliness_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \gamma_2 Y_{i,t} + \gamma_3 \left(Comparability_{i,t} \times Y_{i,t}\right) + \beta X_{i,t} + \varepsilon_{i,t}$$

where i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable			
	Intraperiod Timeliness			
VARIABLES	(1)	(2)	(3)	(4)
Comparability SIC	2.192***		2.318***	
	(0.675)		(0.669)	
Comparability TNIC		0.965*		0.920*
		(0.551)		(0.552)
Average Trade Size	-0.116	-0.936*		
	(0.653)	(0.541)		
Trade-to-Order			-0.049	-0.955*
			(0.615)	(0.548)
Comparability × Average Trade Size	0.448	1.697**		
	(1.033)	(0.830)		
Comparability × Trade-to-Order			0.469	1.849**
			(0.968)	(0.836)
SUE	0.013	0.016	0.007	0.012
	(0.045)	(0.046)	(0.045)	(0.046)
Size	0.072***	0.074***	0.071**	0.072***
	(0.027)	(0.027)	(0.028)	(0.028)
Book-to-Market	0.015	0.012	0.021	0.017
	(0.028)	(0.028)	(0.028)	(0.028)
ROA	0.254	0.174	0.258	0.181
	(0.432)	(0.432)	(0.433)	(0.433)
Institutional Ownership	0.178*	0.166	0.183*	0.171
	(0.104)	(0.105)	(0.104)	(0.104)
No. of Analysts	0.009	0.014	0.016	0.020

	(0.026)	(0.026)	(0.026)	(0.026)
Asset Growth	-0.012	-0.025	-0.005	-0.017
	(0.110)	(0.110)	(0.110)	(0.110)
Loss	-0.090**	-0.094**	-0.091**	-0.095**
	(0.040)	(0.040)	(0.040)	(0.040)
Constant	0.578	1.325**	0.499	1.356**
	(0.601)	(0.553)	(0.596)	(0.552)
Year-Quarter FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Observations	68,759	68,291	69,084	68,609
Adjusted R-squared	0.036	0.035	0.036	0.036

Table 11. The Influence of Financial Statement Comparability on Price Discovery, Controlling for Accounting Quality, Product Similarity, and Accounting Complexity

This table reports the relation between Intraperiod Timeliness and comparability using the following regression specification:

$$Y_{i,t} = \alpha_t + \eta_i + \gamma_1 Comparability_{i,t} + \beta X_{i,t} + \varepsilon_{i,t}$$

where i indexes firms; t indexes year-quarter; α_t and η_i represent year-quarter fixed effects and firm fixed effects; X is a vector of control variables that have been shown to be associated with market reaction to quarterly earnings announcements, including Size, Book-to-Market ratio, ROA, Institutional Ownership, No. of Analysts, Asset Growth, Loss; ***Discretionary Accruals*** is added in Columns (1), (2), (7), and (8); ***Product Similarity*** is added in Columns (3), (4), (7), and (8); ***Accounting Complexity*** is added in Columns (5), (6), (7), and (8);ε is a random error term assumed to be possibly correlated within firms (Petersen, 2009). All variables are defined in Appendix 1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable							
	Intraperiod Timeliness							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Comparability SIC	2.575***		2.259***		1.625***		1.969***	
	(0.663)		(0.620)		(0.600)		(0.664)	
Comparability TNIC		1.147***		1.214***		1.864***		1.793***
		(0.538)		(0.521)		(0.526)		(0.533)
Discretionary Accruals	-0.011	-0.011					-0.016	-0.014
	(0.011)	(0.011)					(0.013)	(0.013)
Product Similarity			0.002	0.003			-0.011***	-0.012***
			(0.006)	(0.006)			(0.003)	(0.003)
Accounting Complexity					0.183***	0.179***	0.173***	0.168***
					(0.054)	(0.054)	(0.056)	(0.056)
Constant	0.468	1.339**	0.508	1.151**	-1.147***	-1.317***	-1.313***	-1.208***
	(0.608)	(0.560)	(0.587)	(0.551)	(0.424)	(0.398)	(0.462)	(0.407)
Year-Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70,508	70,024	73,098	72,884	19,701	19,553	18,687	18,613
Adjusted R-squared	0.038	0.037	0.037	0.037	0.016	0.016	0.017	0.017