How Much New Information Is There in Earnings?
Corporate Decision-Making and Quantitative Analysis
Winter 2024/25 - Individual Report

Melisa Mazaeva

Jan 26, 2025

Abstract

This project uses the TRR 266 Template for Reproducible Empirical Accounting Research (TREAT) to provide infrastructure for open science-oriented empirical projects. Leveraging data from the CRSP and Compustat databases via WRDS, alongside Worldscope and Datastream via Thomson/Refinitiv, this repository showcases a reproducible workflow integrating Python scripts for data preparation, analysis, and visualization. Integrating multiple databases adds complexity, requiring a detailed understanding of their structures and careful scripting to extract, align, and analyze data effectively. The project replicates and extends Ball and Shivakumar (2008) to analyze the informativeness of quarterly earnings announcements and their contribution to annual share price movements, highlighting their critical role in investment decisions and impact on investors, analysts, and policymakers. Key tasks include replicating and comparing original results, extending the analysis to 2007–2023, and applying the methodology to a non-U.S. country. The project also documents research design choices, discusses variations between original and reproduced results, and provides insights into earnings informativeness across different timeframes and jurisdictions. Additionally, it sketches a research design for a non-archival study to evaluate the paper's findings. This code base, adapted from TREAT, demonstrates how the template applies to this project and serves as a structured guide for reproducible empirical research in accounting.

Table of contents

List of Figures

List of Tables

1 List of Abbreviations

CRSP: Center for Research in Security Prices

CQA: Corporate Decision-Making and Quantitative Analysis

DV: Dependent Variable

HU: Humboldt-Universität zu Berlin

IV: Independent Variable

EU: European Union ##

IDE: Integrated Development Environment

TREAT: TRR 266 Template for Reproducible Empirical Accounting Research

UK: United Kingdom ##

US:: United States

WRDS: Wharton Research Data Services

2 Introduction

The aim of this paper is to illustrate the use of open science tools in empirical accounting research. This project builds on the methodological framework established in the Corporate Decision-Making and Quantitative Analysis (CQA) course, which explored a range of empirical research methods—including archival analysis, field experiments, and survey-based approaches—to develop a comprehensive understanding of corporate decision-making and quantitative analysis. Expanding on prior empirical research conducted in Assignments I and II, this paper extends the empirical focus of the course. Assignment I examined audit market concentration in the EU using Transparency Reports data, offering insights into the dominance of major audit firms and the structure of the European audit market. Assignment II explored the economic implications of corporate financial reporting, focusing on Graham, Harvey, and Rajgopal (2005) to analyze managerial decision-making, earnings management strategies, and voluntary disclosure practices. This study highlighted the trade-offs between short-term earnings predictability and long-term firm value and provided a foundation for understanding corporate incentives in financial reporting.

Building on these foundations, Assignment III investigates the informativeness of quarterly earnings announcements and their contribution to annual share price movements. The project replicates and extends Ball and Shivakumar (2008), assessing the extent to which earnings releases serve as a source of new information for financial markets. By integrating multiple datasets from WRDS and applying an event-study methodology, this study evaluates the economic role of earnings disclosures in market efficiency, showcasing the valuation purpose of accounting. At the same time, earnings reports may play a crucial role in contracting by influencing managerial compensation, debt agreements, and other contractual mechanisms tied to financial performance (Ball and Shivakumar 2008). The integration of multiple databases adds complexity, requiring a detailed understanding of their structures and careful scripting to extract, align, and analyze data effectively. Key tasks include replicating and comparing original results, extending the analysis to data from 2007–2023, and applying the methodology to a non-U.S. country to explore cross-market variations.

Beyond empirical replication, the project also documents research design choices, replication steps, and explicit assumptions made whenever the original paper was unclear on how to proceed. It discusses variations between original and reproduced results and provides insights into the timeliness and market impact of earnings announcements across different timeframes and jurisdictions. Additionally, it sketches a research design for a non-archival study to evaluate the paper's findings through an alternative methodological lens. This project leverages the TRR 266 Template for Reproducible Empirical Accounting Research (TREAT) to establish an open science-oriented infrastructure, ensuring transparency, replicability, and structured workflows for empirical accounting research.

Earnings announcements provide investors with valuable information about a firm's market value, with stock prices reacting significantly when earnings news deviates from expectations (Fink 2021, 2). The seminal study by Ball and Brown (1968) was the first to document this relationship, showing that stock prices anticipate earnings surprises, with most of the market reaction occurring before the official announcement, suggesting that earnings reports primarily confirm rather than introduce new information. Over the past decades, more than a thousand studies have examined the interplay between capital markets and financial statements, a research stream that originated with Ball and Brown (1968) (Kothari 2001). This reinforces the role of earnings announcements as a crucial source of financial information.

Building on this foundation, the original study by Ball and Shivakumar (2008) investigates the extent to which quarterly earnings announcements contribute new information to the market, assessing their role in shaping annual share price movements. By estimating the R^2 from regressions of annual stock returns on earnings announcement window returns, the paper quantifies the informativeness of earnings releases, finding that they account for only 1% to 2% of total annual volatility. This challenges the assumption that earnings provide substantial new information and instead suggests a confirmatory role in financial reporting, reinforcing prior market expectations rather than acting as a primary source of new insights. Unlike traditional event studies that assume market efficiency, Ball and Shivakumar (2008) allow for potential market mispricing by not imposing a unit slope restriction in their regressions, meaning that their approach can capture under- or overreaction to earnings announcements. They also emphasize that extending the event window beyond the earnings announcement period would shift the research focus from earnings "surprise" to broader financial reporting effects, such as its role in debt contracting and executive compensation. The study further documents an increasing trend in earnings informativeness in recent years, potentially linked to regulatory changes, shifts in analyst activity, or broader market conditions.

While Ball and Shivakumar (2008) provide key insights into the informativeness of earnings announcements, their study was conducted within a specific timeframe and market context. Since then, financial markets have undergone significant changes due to regulatory reforms, economic crises, and technological advancements in financial information processing. Moreover, the extent to which earnings informativeness varies across international markets remains underexplored. By replicating their study with updated data from 2007–2023 and applying the methodology to a non-U.S. country, this project reassesses the robustness of their findings, examines long-term trends, and evaluates cross-country differences in earnings informativeness. Through this approach, it critically evaluates the generalizability of the original results and provides further insights into the economic role of earnings announcements in financial markets, offering a contemporary perspective on their evolving informativeness and implications for investors, analysts, and policymakers.

The paper is structured into sections corresponding to Tasks 1–3 (Section 3, Section 4, Section 5), each detailing the research design choices and assumptions, documenting the replication steps, and analyzing the replication results for the respective segment. Section 3 follows an exact replication approach by replicating key tables and figures from the original study using US data (1972–2006) to establish baseline results. Section 4 extends the analysis through empirical generalization, applying the same methodology to 2007–2023 US data to compare how results evolve over time. Section 5 employs a generalization and extension approach by applying the methodology to a non-US country, requiring adjustments for different databases and market structures. This framework aligns with the replication taxonomy outlined by Salterio, Luo, and Adamson (2022). Finally, Section 6 sketches the survey design as a non-archival study that allows evaluating the key findings of the seminal paper, following Bloomfield's (2016) triangulation principle. The concluding remarks are provided in Section 7. The entire Python computation code for return calculations is available in `code/python/do_analysis.py` for detailed review if necessary. This paper focuses on the replication process, presenting visualizations, and discussing the results.

3 Task 1 - Replication of Key Tables and Figures

Task 1 is the most comprehensive, replicating the methodology of key tables and figures from Ball and Shivakumar (2008) using daily US stock return data (1972–2006) to establish baseline results, ensuring alignment with the original findings before extending the analysis in Section 4. By reconstructing Table 1 (Panel A), Table 2 (all panels), and Figure 1 (all panels), this task evaluates the robustness of the original results and identifies potential discrepancies, offering insights into data consistency, methodology, and market dynamics over the examined period. The use of daily CRSP data is essential for capturing short-term stock price movements around earnings announcements, ensuring precise event window calculations. The discussion of replication findings is presented in Section 3.3.

3.1 Research Design Choices and Assumptions

Following Ball and Shivakumar (2008), I focus the analysis on earnings announcements and stock returns from 1972 to 2006, ensuring that the data accurately reflects the original study's methodology and findings. The replication aims to mirror the research design as closely as possible with the available data, maintaining consistency in sample selection, event window definitions, and return calculations.

Based on the original paper, I do not gather analyst expectations or estimate earnings deviations for my replication. Instead, I only require stock return data and earnings announcement dates, which simplifies the data collection process.

Same as Ball and Shivakumar (2008), I group earnings announcements based on their actual announcement dates rather than the fiscal periods they cover. Since Compustat provides the precise earnings announcement date and CRSP aligns stock returns with trading days, this approach ensures consistency with the original study. No adjustments are made to realign quarters.

In addition, I impose the following assumptions to ensure clarity and consistency where Ball and Shivakumar (2008) do not provide explicit guidance:

1. Following Ball and Shivakumar (2008), I define earnings announcement windows as the three-day period surrounding the earnings release (-1 to +1), where Day -1 is the last trading day before the announcement, Day 0 is the announcement day, and Day +1 is the first trading

day after the announcement. According to Center for Research in Security Prices (CRSP) (2024) guide, data are never provided on weekends or trading holidays, meaning there is no need for manual filtering of such days. However, if an earnings announcement falls on a non-trading day, adjustments are necessary to maintain the three-day window. Hence, earnings announcement dates are first extracted from Compustat and then matched with CRSP trading data to obtain stock returns for the event window (-1, 0, +1). If Day 0 falls on a weekend or holiday, it is shifted to the next available trading day. Similarly, if Day -1 or Day +1 is unavailable due to a non-trading day, the nearest prior or next trading day, respectively, is used to preserve the event window. This adjustment prevents shortening the window, ensuring a complete three-day period for capturing the full market response to earnings announcements.

2. As in the original paper, firm-years are selected based on available stock return data in CRSP. While Ball and Shivakumar (2008) restrict the sample to firms with at least 240 trading days per year, I follow the course guidance and do not apply this restriction, allowing for a slightly larger sample size. This adjustment should be considered when interpreting differences from the original study.
3.

By following the steps outlined in Section 3.2 and adhering to the assumptions made, I successfully replicated the results from Ball and Shivakumar (2008). A thorough step-by-step approach, with each step clearly documented, helps to understand and verify the outputs.

---

1. The original report references the reports prepared by national competent authorities (NCAs) responsible for audit oversight as the main source of data, where the data refers to the years 2020 and 2021 and was collected in 2022 (**EC_Report_2024?**). However, this replication uses data obtained from the Audit Analytics Transparency Reports database via WRDS, which provides the latest available version as of September 2024, updated quarterly (**WRDS_Audit_Analytics_Transparency_Reports?**). Due to potential adjustments and updates made to the database since the original data collection period, there may be differences that could affect the results. For example, audit firms may disclose updated information in subsequent reports, which would be reflected in the later database version rather

than the historical snapshot used in the original report. Furthermore, the data vendor regularly updates its databases to correct errors and add new information, which may be included in the later data but not in the 2022 snapshot.

2. For the purpose of replicating Figure 3, I use the `report_year` variable as the primary filter to define the relevant data for year 2021. This choice is based on the fact that `report_year` represents the idealized fiscal year of the Transparency Report, based on the *Europe Transparency Reports Data Dictionary* by Wharton Research Data Services (**Europe_Transparency_Reports_Data_Dictionary?**), which aligns directly with the year-based aggregation needed for Figure 3. While the `report_period_end_date` provides the exact end date of each reporting period (**Europe_Transparency_Reports_Data_Dictionary?**), using `report_year` allows for a consistent, annual aggregation without requiring additional alignment of various period end dates. This approach simplifies the data extraction and ensures that all entries correspond to the fiscal year 2021. Since the report does not specify the choice of variables used from the database, this could cause differences in the results.

3.2 Replication Steps

The analysis involves gathering and filtering Transparency Report data, identifying relevant PIEs and EU countries, and calculating the Big 4, CR4, and 10KAP market shares for each country as well as at the EU level.

The replication process includes data loading, preparation, and cleaning, followed by the computation and visualization of market concentration measures. For Assignment I, I pulled data from the Audit Analytics database via WRDS and used the Python programming language to carry out the empirical analysis. Visual Studio Code was used as the Integrated Development Environment (IDE) for writing, debugging, and optimizing the Python code.

The replication is based on data pulled from the Audit Analytics Transparency Reports database, specifically from `audit_europe.feed76_transparency_reports` table, which was filtered and aggregated for the analysis. The table offers Transparency Reports published annually by audit firms based in the EEA and Switzerland, along with the names of all entities listed in each audit firm's Transparency Reports (**WRDS_Audit_Analytics_Transparency_Reports?**).

Step 1: Pulling the Data and Managing the Database

This Assignment involves pulling data directly from the Audit Analytics database and preparing the data for further analysis from raw data to final output.

To ensure data relevance, the pulling process was restricted to data for the year 2021. The variable `trans_report_auditor_state` was used to filter the data to include only audit firms associated with the specific EU and EEA countries, as specified in configuration file `config/pull_data_cfg`. This filtering step ensured that the analysis focuses on audit market concentration within the geographical scope and year range as defined by (**EC_Report_2024?**).

Step 2: Data Preparation

The raw Transparency Report dataset initially contained 13,385 observations, representing entries for the year 2021. To ensure consistency with (**EC_Report_2024?**), the abbreviation 'GR' for Greece was replaced with 'EL' in the trans_report_auditor_state field, affecting 188 rows.

The `number_of_disclosed_pies` variable provides the clearest indication of statutory audits conducted by each auditor for PIEs. The definition of PIEs varies across EU and EEA countries (**AccountancyEurope_PIE_2017?**), but if Transparency Reports consistently follow country-specific definitions, using the provided variable is reasonable. An important verification step involved comparing the reported `number_of_disclosed_pies` with the count of unique `entity_map_fkey` entries for each `transparency_report_fkey`. This analysis revealed that 5,696 transparency reports included fewer entities in the dataset than the disclosed PIEs, suggesting that some PIE entities might be missing from the dataset. This discrepancy reflects missing PIE data rather than the inclusion of non-PIE entities, hence it is assumed that all entities in the dataset are PIEs, maintaining consistency in the framework for analysis.

Additionally, missing values in key fields, including `transparency_report_fkey`, `entity_map_fkey`, `auditor_fkey`, and `trans_report_auditor_state`, were checked, and it was confirmed that no rows needed to be removed due to missing data, ensuring the completeness of the dataset. To focus on relevant data, rows with `number_of_disclosed_pies` equal to or less than zero were filtered, but no such rows were identified, and all observations were retained.

Duplicate entries in the `entity_map_fkey` column were then analyzed, revealing 1,011 duplicate entities. I assume that duplicate entries in the dataset do not introduce significant issues for the replication of Figure 3. Duplicate entries for the same entity are expected in cases where an entity is audited by multiple audit firms or networks, potentially as part of a joint audit. Since these duplicates retain consistent information on `trans_report_auditor_state`, they do not distort country-level distributions. Additionally, while duplicates might expand representation across different auditor networks or groups, the essence of Figure 3 — focusing on aggregate distributions — remains unaffected. Therefore, these duplicates were not removed.

Auditor network names were standardized to ensure consistency, with names like `|Mazars Worldwide|Praxity Global Alliance|` simplified to `|Mazars Worldwide|`, for example. This standardization helped avoid double-counting and unify same entries under consistent naming conventions.

Audit firms were then categorized into groups, including the Big 4 (Deloitte, EY, KPMG, and PwC), the 10KAP (which includes the Big 4 along with other major networks listed in **?@sec-research_design_assumptions**), 'Unaffiliated' firms (those outside the Big 4 and 10KAP). The `auditor_network` field contained 636 observations with missing values, which were grouped under the "Other (Blank)" category. I assume that these blank entries do not belong to the Big Four or 10KAP networks but may still contribute to the CR4 category in some countries. So, these entries were retained in the dataset and reviewed during the aggregation stage to validate their relevance.

These preparation steps ensured alignment with the methodology of (**EC_Report_2024?**) and the dataset's readiness for subsequent analysis.

Step 3: Analysis Implementation and Reproduction of Tables and Figure

The analysis step computes market concentration metrics for audit firms across EU countries and at the EU level using the prepared transparency data. The analysis begins by calculating the market shares of the Big 4, 10KAP, and CR4 audit firm groups for the number of statutory audits conducted in 2021. For each country, the Big 4 market share is derived as the percentage of PIE statutory audits conducted by Deloitte, EY, KPMG, and PwC, while the CR4 market share represents the top four audit firms in each country based on audit counts. The 10KAP market share includes the Big 4 along with six additional networks, providing a broader view of market concentration.

The following formula is used to calculate market share:

$$\text{Market Share (\%)} = \left(\frac{\text{Number of PIE Audits by Network Group}}{\text{Total PIE Audits in Country}}\right) \times 100$$

The analysis also includes the creation of a bar chart visualizing market shares for all countries and the EU aggregate, saved in both PNG and pickle formats. The aggregated market share data is saved in CSV format, ensuring reproducibility and further analysis opportunities.

3.3 Results

Comparing the replication results of Figure 1 (see **?@fig-market-shares**) with those from Ball and Shivakumar (2008) (see Figure 1 below) reveals both similarities and discrepancies.

[Figure 1 about here.]

we confirm? "The results are consistent with the view that the primary economic role of reported earnings is not to provide timely new information to the share market. By inference, that role lies elsewhere, for example, in settling debt and compensation contracts and in disciplining prior information,including more timely managerial disclosures of information originating in the firm's accounting system. The comparatively low "surprise" content of earnings announcements is to be expected, for a variety of reasons. By its nature, accounting earnings is low frequency (quarterly), not discretionary (announced every quarter, independent of whether there is substantial new information to report), and primarily backward-looking. Other information, and hence revision in share price, is comparatively high frequency, frequently discretionary (released only when there is substantial information to report), and both forward-looking and backward-looking."

##**?@fig-market-shares** illustrates the market shares of audit firms — Big 4, CR4, and 10KAP — for the number of PIE statutory audits conducted in 2021. Countries are sorted in a specific order reflecting the replication of Figure 3 from the European Commission's 2024 report. To verify the results of analysis step and observe trends before plotting, I have additionally saved the CSV output in `aggregated_market_shares.csv`. The analysis of market shares for statutory audits across European countries reveals distinct patterns of market concentration and auditor dominance. Big 4 firms exhibit a significant presence, often commanding a dominant share in many countries. For example, countries such as the Czech Republic, Estonia, and Finland demonstrate Big 4 market shares exceeding 95%, reflecting the significant influence of these firms in specific markets. However, the extent of this dominance varies, with lower Big 4 shares observed in countries like Bulgaria (17.5%) and Greece (43.6%), indicating a more diversified audit market in these regions. The analysis reveals that the Big 4 hold a market share exceeding 80% in 11 EU countries. This aligns with rthe finding of (**EC_Report_2024?**), which similarly highlights that the Big 4 dominate over 80% of the market share in 11 Member States.

The inclusion of additional audit networks through the 10KAP grouping increases the market share substantially across all countries, as expected. This is particularly evident in countries like Ireland, Malta, and the Netherlands, where the 10KAP share reaches 100%, reflecting the full inclusion of statutory audits under this grouping. In contrast, countries like Bulgaria and Poland, with 10KAP shares of 41.8% and 63.6%, respectively, suggest the presence of a substantial number of statutory audits conducted by unaffiliated or smaller firms.

In the analysis of CR4 market shares, I verified whether the four largest audit firms (CR4) in each country overlapped entirely with the Big 4 audit firms. This overlap occurred in 15 out of 28 countries, where CR4 and Big 4 market shares were identical. In the remaining 13 countries, at least one non-Big 4 firm contributed significantly to the statutory audits, resulting in distinct CR4 market shares. These findings align with (**EC_Report_2024?**), which notes that in 13 Member States, the Big Four are not the four largest audit firms in terms of the total number of PIE statutory audit opinions. This highlights the gradual diversification in the audit market in some countries, where non-Big 4 firms are playing a more prominent role, while the Big 4 continue to dominate in others.

At the EU level, the aggregated market shares further underscore the dominance of these major players. The Big 4 account for 70% of statutory audits, compared to (**EC_Report_2024?**), which notes an average EU market share of 59% for the Big 4 in 2021, down from 70% in 2018. The broader 10KAP grouping in my output reaches nearly 90%, exceeding the 81% reported by (**EC_Report_2024?**). The CR4 market share at the EU level also stands at 70%, aligning with the Big 4, and is consistent with the average CR4 market share reported by (**EC_Report_2024?**). These results highlight the varying degrees of market concentration across Europe, with certain countries demonstrating a highly centralized audit market dominated by the Big 4, while others display a more distributed market landscape, incorporating both major and smaller audit firms. The slight discrepancies in the figures suggest potential differences in methodologies, data coverage, or sample definitions.

Based on the results for Austria, the Big 4 market share is 86.7% in my analysis, aligning closely with the approximate 85% represented in bar chart of (**EC_Report_2024?**). Similarly, the 10KAP market share of 92.55% in my analysis corresponds well with the slightly higher bar in the report, and the CR4 market share of 86.7% aligns perfectly with the Big 4 share, confirming the dominance of these firms in Austria's audit market. This consistency highlights the robustness of the replicated analysis for this country.

The results for Romania show notable discrepancies. The EC Report indicates market shares of 15% for the Big 4, 16% for CR4, and 24% for 10KAP, while my analysis reports significantly higher values: 63%, 70.61%, and 78.38%, respectively. These differences likely arise from assumptions made in **?@sec-research_design_assumptions** like variations in PIE definitions and auditor classifications. The report by (**EC_Report_2024?**) may use stricter criteria, reflecting Romania's decentralized market where non-Big 4 firms dominate, unlike the broader inclusion in my dataset.

In summary, the replication effectively captures the original report's key findings, confirming the dominance of the Big 4 and the broader 10KAP group in the European audit market. The analysis highlights varying degrees of market concentration across countries, with some demonstrating a more decentralized audit landscape. While discrepancies in individual country results, such as Romania, underline the importance of methodological alignment, the strong similarity between the overall market shares reported in the original report and the replicated results underscores the robustness and reliability of the findings.

4 Task 2 - Extending the Analysis to 2007–2023

This Section extends the analysis to 2007–2023, a period defined by major economic events such as the 2008 financial crisis and the COVID-19 pandemic, which may have influenced the informativeness of earnings announcements. While the task is relatively straightforward in terms of programming—requiring adjustments to the sample period—it demands careful economic interpretation of observed trends, market shifts, and potential structural changes that may influence the relationship between earnings announcements and stock returns.

4.1 Research Design Choices and Assumptions

Assumptions from Section 3.1 still hold

4.2 Replication Steps

4.3 Results

5 Task 3 - Cross-Country Replication

Task 3 extends the analysis beyond the United States by replicating Figure 1 using data from a non-U.S. market, providing insights into how earnings informativeness varies across different regulatory environments and market structures. This task requires mapping variables from CRSP/Compustat to their equivalents in Worldscope/Datastream, adjusting for differences in accounting standards, market liquidity, and institutional factors. While the core replication methodology remains the same, careful data handling and economic interpretation are crucial to account for cross-country differences.

5.1 Research Design Choices and Assumptions

It is important to use same logic in defining event windows as in Task 1 to ensure consistency https://community.developers.refinitiv.com/discussion/106705/how-to-get-only-trading-days-in-datastream-data/p1?tab=accepted country-specific market calendars ?

We need to check whether non-US databases (Worldscope/Datastream) use the same announcement date convention or if they report earnings by fiscal period.

5.2 Replication Steps

5.3 Results

6 Task 4 - Research Design for a Non-Archival Study

The research design follows the generalization goal in empirical literature, emphasizing the need to validate findings across different methods (Bloomfield, Nelson, and Soltes 2016). Ball and Shivakumar (2008) assess earnings informativeness through stock price reactions, but triangulation—beyond replication—requires diverse methods to examine the same question (Bloomfield, Nelson, and Soltes 2016, 353). While price reactions indicate market response, they do not capture investor perceptions. A survey directly evaluates whether market participants view earnings announcements as confirmatory or informative. If investors confirm a secondary role, it reinforces Ball and Shivakumar's (2008) findings, ensuring informativeness reflects cognitive and behavioral mechanisms rather than price fluctuations. These insights could inform corporate reporting strategies by clarifying how investors prioritize disclosures.

A survey is the most suitable non-archival method, capturing investor sentiment beyond what archival data provides. Unlike lab experiments, which lack real-world applicability, surveys measure the dependent variable (DV) by eliciting participant perceptions (Bloomfield, Nelson, and Soltes 2016, 358). Field experiments, though capturing real-time reactions, require direct intervention, posing ethical and logistical challenges. A long-term research program combining surveys and field studies would enhance validity, leveraging unlimited funds to assess investor decision-making and market responses.

To ensure survey reliability, design strategies follow Brüggemann and Worku (2024). A sample of 300 investors, analysts, and financial professionals will provide institutional and retail perspectives while balancing statistical power and feasibility. The survey will be distributed via email through financial networks, investor associations, and professional platforms (e.g., LinkedIn, CFA societies) and in paper format at finance conferences. The Humboldt-Universität zu Berlin (HU) brand may be used, subject to approval. Respondents will be assured confidentiality and offered an €20 honorarium. A pilot study with 30 participants will refine question clarity, survey length, and response distribution, helping identify unclear or missing questions and assess completion time.

To minimize response bias, questions will be neutrally worded to capture pre- and post-announcement perceptions. The fully anonymous survey ensures candid responses without requiring personal financial history.

The **DV** is the perceived informativeness of earnings announcements, measured through survey responses on whether they are confirmatory or informative. Independent variables (**IVs**) include investor preparation, market awareness, reaction timing, perceived novelty of earnings, key financial indicators, and external conditions. These are measured via Likert-scale, ranking, and multiple-choice questions, supplemented by qualitative insights from follow-up interviews.

To deepen findings, selected participants will be invited for confidential follow-up interviews, ensuring diversity in investment strategies, industries, and expertise. These interviews will be conducted via video conferencing or phone calls. The following sections provide detailed sketches of the survey and interview designs.

6.1 Survey Questions

1. **How do you typically prepare for earnings announcements in your investment decisions?**
   - I conduct in-depth research and adjust my positions in advance
   - I monitor but rarely adjust positions pre-announcement
   - I rely on market consensus, analyst forecasts, and AI-driven insights
   - I do not make investment decisions based on earnings announcements
2. **How do you typically react to earnings announcements?**
   - I adjust my investment strategy immediately based on the announcement.
   - I wait for further analysis before making changes.
   - I rarely make investment decisions based on earnings announcements.
3. **To what extent do you believe that earnings announcements provide new information beyond what is already reflected in market prices?**
   - Always
   - Most of the time
   - Sometimes
   - Rarely
   - Never
4. **Rank the following factors in order of importance when evaluating earnings announcements (1 = most important, 5 = least important):**
   - Earnings per share (EPS) compared to analyst forecasts
   - Revenue growth
   - Management guidance and commentary
   - Market reaction on the day of the announcement
   - Industry trends and macroeconomic conditions
5. **Do you consider earnings announcements to be more confirmatory or informative?**
   - Primarily confirmatory (reinforce existing expectations)
   - Primarily informative (provide new insights)

- A mix of both

6.2 Follow-Up Interview Questions

1. Can you describe a recent instance where an earnings announcement significantly influenced your investment decision?
2. In your experience, are there specific industries where earnings announcements are more informative than confirmatory?
3. Do you use earnings announcements differently depending on market conditions (e.g., economic downturn vs. growth periods)?

7 Conclusion

This project effectively demonstrates the use of a systematic and collaborative workflow for empirical accounting research, leveraging the TRR 266 Template for Reproducible Empirical Accounting Research. By following an open science approach, I successfully replicated key tables and figures from Ball and Shivakumar (2008), providing insights into how earnings announcements contribute to price formation and market efficiency. While exact replications often yield different samples and outcomes due to dataset updates or methodological variations, my results align closely with the statistics presented in the original study, reinforcing the reliability of the replication process. Moreover, by extending the analysis beyond the original study's U.S. market focus, the project highlights how market structures and investor behaviors influence the informativeness of earnings disclosures in different jurisdictions.

The study contributes to the ongoing discussion on market efficiency and the economic role of corporate disclosures by providing empirical evidence on how earnings informativeness has evolved over time and across jurisdictions. The cross-country analysis highlights variations in market responses to earnings announcements, suggesting that institutional factors, market structures, and investor behavior play a role in shaping how financial information is processed. These findings have implications for investors, analysts, and policymakers, as they underscore the importance of regulatory consistency and market transparency in shaping the effectiveness of financial reporting.

This assignment required a comprehensive application of programming skills and institutional knowledge gained throughout the course, integrating data analysis, replication, and visualization techniques in line with open science principles. In the future, this repository can be cloned or forked (if made public) to facilitate further research on earnings informativeness, enabling additional extensions or robustness tests. Additionally, the survey developed as part of the non-archival study proposal can be further refined and expanded, providing a structured framework for gathering primary data on market participants' interpretations of earnings announcements. Through this approach, the study not only revisits a fundamental question in financial research but also provides a foundation for future empirical investigations into the evolving role of earnings announcements in global capital markets, both through archival and non-archival methodologies. Thanks for reading!

References

Ball, Ray, and Philip Brown. 1968. "An Empirical Evaluation of Accounting Income Numbers." *Journal of Accounting Research* 6 (2): 159. https://doi.org/10.2307/2490232.

Ball, Ray, and Lakshmanan Shivakumar. 2008. "How Much New Information Is There in Earnings?" *Journal of Accounting Research* 46 (5): 975–1016. https://doi.org/10.1111/j.1475-679X.2008.00299.x.

Bloomfield, Robert, Mark W. Nelson, and Eugene Soltes. 2016. "Gathering Data for Archival, Field, Survey, and Experimental Accounting Research." *Journal of Accounting Research* 54 (2): 341–95. https://doi.org/10.1111/1475-679X.12104.

Brüggemann, Ulf, and Fikir Worku. 2024. "Corporate Decision-Making and Quantitative Analysis: Empirical Methods - Survey; Introduction to Assignment II." Humboldt University Berlin. https://moodle.hu-berlin.de/pluginfile.php/6320269/mod_resource/content/5/cqa_winter2425_session7.pdf.

Center for Research in Security Prices (CRSP). 2024. "CRSP US Stock & Index Databases - Data Descriptions Guide." Graduate School of Business, University of Chicago. https://www.crsp.org/wp-content/uploads/guides/CRSP_US_Stock_&_Indexes_Database_Data_Descriptions_Guide.pdf.

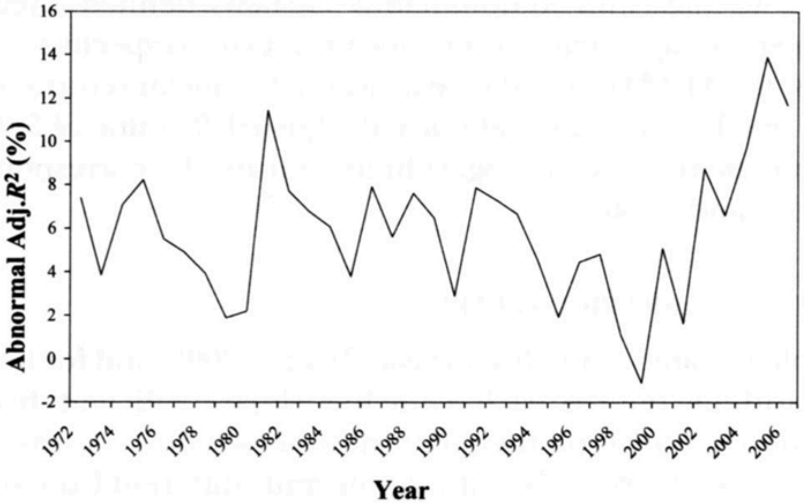
Fink, Josef. 2021. "A Review of the Post-Earnings-Announcement Drift." *Journal of Behavioral and Experimental Finance* 29 (March): 100446. https://doi.org/10.1016/j.jbef.2020.100446.

Graham, John R., Campbell R. Harvey, and Shiva Rajgopal. 2005. "The Economic Implications of Corporate Financial Reporting." *Journal of Accounting and Economics* 40 (1): 3–73. https://doi.org/https://doi.org/10.1016/j.jacceco.2005.01.002.

Kothari, S. P. 2001. "Capital Markets Research in Accounting." *Journal of Accounting and Economics* 31 (1-3): 105–231. https://doi.org/10.1016/S0165-4101(01)00030-1.

Salterio, Steven E., Yi Luo, and Constance Adamson. 2022. "Replication of Audit and Financial Accounting Research: We Do a Lot More Than We Think." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4210603.

Panel A: Abnormal adjusted R^2 values from annual cross-sectional regressions of calendar-year arithmetic returns on arithmetic returns at the four quarterly earnings announcements in the calendar year



Panel B: Slope coefficients from annual cross-sectional regressions of calendar-year arithmetic returns on arithmetic returns at the four quarterly earnings announcements in the calendar year

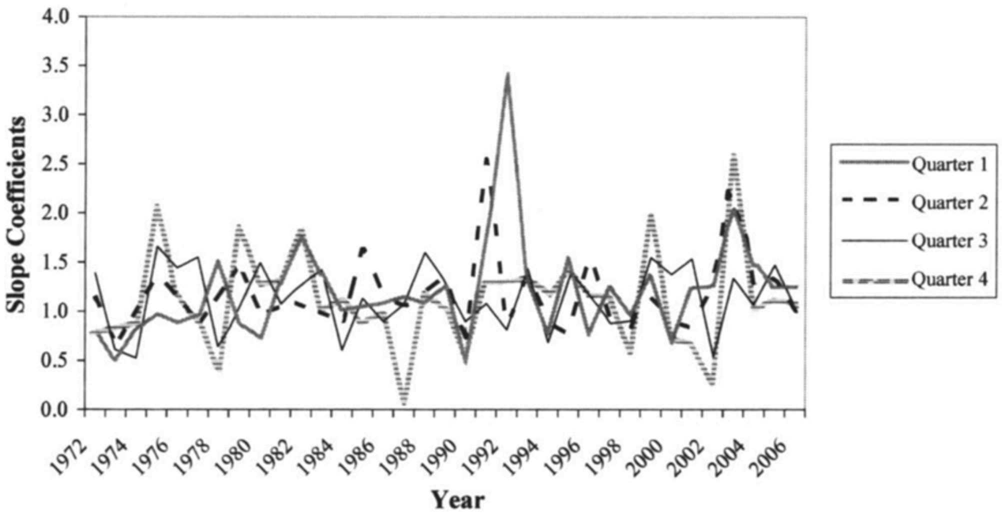


FIG. 1.—Abnormal adjusted R^2 values and slope coefficients from annual 1972 to 2006 cross-sectional regressions of calendar-year returns on returns at the four quarterly earnings announcements. Calendar-year buy-and-hold returns are computed from daily CRSP returns. Earnings-announcement returns are buy-and-hold returns for the three days surrounding the Compustat announcement date. The sample is all firm-years with available data on the quarterly Compustat and daily CRSP files. Firm-years with other than four earnings announcements or with daily returns data for fewer than 240 trading days are excluded.

Figure 1: Original Figure 1 from Ball and Shivakumar (2008)