Private Firm Information Dissemination and Analysts' Public Firm Forecast Accuracy

ABSTRACT

We examine the effect of private firm information dissemination on analysts' forecast accuracy for public firms, utilizing the mandatory adoption of electronic business registers (EBR) in EU countries as a (plausibly) exogenous shock. Our findings reveal a significant improvement in analysts' earnings forecast accuracy following the EBR implementation that enhanced private firms' information dissemination, indicating positive information spillovers to public firms. This effect is more pronounced (i) when private firm disclosures are timelier within the context of the focal public firm's fiscal year and (ii) when the focal public firm has private firm suppliers, customers, or competitors. However, increased transparency of private firms also reduces analysts' incentives to cover public firms, as investor attention shifts from public to private firms. This countervailing force negatively impacts analyst forecast accuracy, partially offsetting the positive effects from information spillovers.

Keywords: private firm transparency, information dissemination, analyst forecast, public firms, information spillover

Data availability: The data used in this study are publicly available from the sources identified in the paper.

1. Introduction

We study the effect of private firms' information transmission—an essential aspect of their transparency—on financial analysts' earnings forecast accuracy for public firms. Private firms collectively constitute the majority of the world economy.[1] Yet, there is limited understanding of how analysts utilize private firm information when they analyze and forecast public firms' business operations. Prior research has explored the costs and benefits of private firms' information transparency mainly from the perspective of private firms themselves (Bernard 2016; Breuer 2021; Baik, Berfeld and Verdi 2025; Ortiz, Peter, Urzua and Volpin 2023). However, beyond the impact on private firms, there are likely spillovers on other parties within an economy. Given that private firms have relatively few outside stakeholders, the direct benefit of improving their information transparency seems relatively low (Minnis and Shroff 2017). This makes it particularly pertinent to understand the information externalities that private firms generate beyond themselves.

In this study, we examine how private firm transparency influences analysts' earnings forecasts for public firms. For identification, we employ the staggered implementation of electronic business registers (EBR) in EU member countries under Directive 2003/58/EC, which requires that limited-liability firms use centralized EBRs to file their mandated financial statements in accordance with the relevant disclosure regulations and make them available online.[2] Previously, obtaining private firms' filings

[1] For example, based on the universe of firms in the Bureau van Dijk Orbis database during 2000-2019, 99.5% of all reporting firms around the world were private firms, and they collectively generated 50.2% of total sales and employed 57.3% of the workforce.

[2] Activities intended to streamline and standardize EU country-level business registers saw their origins in 1992 with the first attempt at a European Business Register that would ensure easy, multi-lingual access to official company data in country registers. However, progress in improving access to EU country-level business registers was slow and cumbersome (European Commission, 2009). This led to the issuance of Directive 2003/58/EC of the European Parliament and of the Council of 15 July 2003, which amended Council Directive 68/151/EEC. The directive mandated that all filings, whether submitted by paper or electronic means, be entered into the register in electronic form.

was typically inconvenient and time-consuming.[3] The adoption of the new filing system substantially cuts down the time and effort required to access such information. We stress that in this setting, the underlying force driving firm transparency is information dissemination, which is distinct from disclosure levels. Importantly, the directive is not expected to materially impact public firms, whose disclosures are already readily accessible through company websites, financial intermediaries, and stock exchanges.

We focus on private firms' information externalities as manifested through analysts' public firm earnings forecasts, for the following reasons. First, analysts as key information intermediaries in capital markets are important users of financial disclosures. Anecdotal evidence suggests that analysts frequently reference private firms in their research reports.[4] However, there lacks a systematic understanding of how analysts utilize private firm information and whether such information significantly impacts their forecasts for public firms. Investigating these aspects allows us to gain insights into the "black box" of analysts' decision-making processes (Ramnath, Rock and Shane 2008; Bradshaw 2011). Second, when aiming to capture information externalities, analyzing analysts' decisions provides distinct advantages over examining firms' decisions. As sophisticated information users, analysts are expected to quickly respond to private firm

[3] For example, in the UK, people would need to physically visit the Companies House (UK's Business Register) offices to request information or send a written request to Companies House by post, The requested documents would then be sent back to them by mail. In Germany, limited-liability firms filed hard-copies of their financial statements with local courts and published them in paper-based newspapers, limiting the interested public's ease and speed of information access (Breuer and Breuer, 2022).With the adoption of the centralized EBR, one may download private firm filings for free or at a minimal fee. Beuselinck, Elfers, Gassen and Pierk (2023) summarize the features of EBRs of the EU Member States.

[4] In the UK for the period 2000-2019, an average of 425 analyst reports per year made explicit reference to private firms. For example, UBS's report for Dunelm Group dated 23 September 2024 (p.11) states "we used financials from both private and publicly listed companies to both build a historical database and forecast our overall market estimate in the future years. For the forecast years, we used UBS estimates (or consensus) for listed companies and our own forecasts for private companies to gauge industry performance in future years." As another example, Barclay's report on Carrefour's dated 20 September 2024 mentions "We examine market share trends in France (where Carrefour's price investments are gaining traction) and the accounts of private peers." Appendix C provides a snapshot of analyst reports mentioning private firms.

information and adjust their forecasts accordingly. In contrast, firms' operations are multifaceted and more complex, with their decisions influenced by many different factors such as transaction costs, financial constraints, and internal governance processes; this complexity complicates efforts to isolate the effects of information externalities.

Drawing on prior literature, we envisage both a direct and an indirect effect of private firm information on analysts' public firm forecasts. The direct effect arises from an enriched information set available to analysts. In principle, information about private firms complements that of public firms, contributing to a more comprehensive understanding of industry dynamics (e.g., Kim, Verdi, and Yost, 2020; Bernard, Blackburne, and Thornock, 2020; Barrios, Choi, Hochberg, Kim, and Liu, 2021). To the extent that private firm information enables analysts to better discern industry trends and opportunities (Ali, Klasa, and Yeung 2009), it enhances their ability to forecast firm performance. In line with this view, research shows that analyst forecasts incorporate not only the financial statement information of the focal firm (e.g., Cen, Chen, Dasgupta and Ragunathan 2021; Gibbons, Iliev and Kalodimos 2021) but also that of industry peers (e.g., De Franco, Hope and Larocque 2015; Han, Hu, Huang and Xue 2021, Brown, Byard, Darrough and Suh, 2024). However, processing private firms' information can entail significant costs. The average private firm is small and often constitutes a tiny part of an industry, making it effort-intensive to extract relevant information. Improved information dissemination facilitates the collection and utilization of disclosed data, enabling analysts to make more accurate forecasts for public firms.

The indirect effect arises from changes in analyst incentives to cover public firms. Theoretical research predicts that as some firms in an economy increase their disclosure of information, capital resource is diverted away from other firms either due to investors' limited information processing capacity (Fishman and Hagerty 1989) or scarce capital supply (Zhang 2013), thus causing resource re-allocation in the economy. Empirical evidence from Kim and Olbert (2022) and Liu, Shi, Zeng and Zhang (2023) supports this prediction. In our context, increased private firm information transparency—owing to more efficient dissemination—makes private firms more attractive as an investment option, which thus diverts capital away from public firms (Kim and Olbert 2022). Consequently, as investor demand for analyst services decreases in the public market, analyst incentives to cover public firms decline, leading to a reduction in forecast accuracy. This indirect effect of improved information dissemination, operating through resource reallocation, offsets the direct effect and may even outweigh it as suggested by the theoretical predictions of Zhang (2013).

To test these predicted effects, we perform a difference-in-differences (DiD) analysis around the implementation of EBRs in EU states. Following Horton, Serafeim and Serafeim (2013), we measure earnings forecast errors as the natural logarithm of the absolute value of the difference between the average analyst earnings forecast and the actual earnings, scaled by the absolute actual earnings.[5] We control for firm-specific characteristics known to be correlated with analyst forecast errors (Dhaliwal, Radhakrishnan, Tsang and Yang 2012), and use firm and year fixed effects to control for time-invariant firm characteristics and time trends that affect analyst earnings forecasts. Standard errors are clustered at the country-year level to ensure that variations in the number of observations across countries and years do not bias our results.

Our baseline results from staggered DiD tests show that analysts' forecast errors for public firms become significantly smaller after a country implements the EBR, as benchmarked against countries that do not implement EBRs. Regression estimates

[5] Our inferences are unchanged if we scale forecast errors by stock price at the beginning of the fiscal year. We take the natural logarithm of analyst forecast errors to mitigate the effect of extreme values.

indicate that on average analysts' earnings forecast errors decrease by about 20% post EBR relative to benchmark firms. This finding shows that overall, the direct effect of improved information dissemination dominates the indirect effect (if any), leading to an overall improvement of analyst forecast accuracy for public firms.

Our results are robust across multiple alternative samples, fixed effect structures, and clustering choices, and to controlling for country-industry-year factors. To address the limitations of staggered DiD design, we also conduct stacked DiD analyses employing more stringent control groups and arrive at the same conclusion. Further analysis shows that the documented effect is more pronounced in industries where private firms provide more extensive disclosures, thereby reinforcing the existence of the dissemination effect, which is contingent on the level of disclosures.

Next, we aim to identify specific reference points that help anchor analysts' evaluations. We posit that information is particularly valuable to analysts when private firms have direct business relationships, or are in direct competition, with the focal public firm being assessed. To explore this, we consider three types of anchoring firms: suppliers, customers, and competitors. Consistent with our expectation, we find that the documented effect of information dissemination is stronger when there exist clearly identifiable private suppliers, customers, or competitors of the focal public firm that are affected by EBR implementation.

To sharpen the evidence on the information dissemination effect, we perform tests that exploit the timing of private firm disclosures. We expect private firm disclosures to be more valuable for analyst forecasting when they are made available in a timelier manner in the context of the focal public firm's fiscal year, as this allows analysts to better understand the economic environment in which the public firm operates. Confirming our expectations, we find that analyst forecast accuracy improves more significantly for public firms whose peer private firms disclose their latest year's financial information earlier, versus later, within the focal public firm's financial year.

Having established that improved dissemination of private firm information increases analysts' forecast accuracy—thereby confirming the direct effect—we next turn our attention to the indirect effect stemming from capital reallocation that results in changes in analyst incentives. Our tests explore evidence manifested, respectively, through private and public equity markets, analysts' activities, and ultimately, forecast accuracy. Supporting the theoretical reasoning, we find that after EBR implementation, private equity (PE) investors allocate more capital to private firms while simultaneously allocating less to public firms. Importantly, although analyst forecast accuracy for public firms improves on average (as discussed above), this effect is significantly diminished in industries that experience, versus those that do not experience, increased PE investments in private firms.

In the domain of public equity markets, our DiD analysis indicates a significant reduction in public firms' financing as well as investors' trading volumes post EBR implementation. Further, this reduction in market activities is accompanied by corresponding decreases in the number of analysts following the public firm and the frequency of forecast issuances, suggesting a diminished need for analyst services. Finally, we show that the positive effect of private firm information dissemination on analyst forecast accuracy is significantly weakened where analyst incentives decline the most. Taken together, our results show that both the direct (informational) effect and the indirect (resource reallocation) effect are present in our setting, and they jointly determine the extent to which private firm information influences analysts' earnings forecasts for public firms.

This study advances our understanding of how private firms' information transparency can generate spillover effects.[6] Research exploring this topic across different contexts has yielded mixed findings. For instance, Kim and Olbert (2022) find that increased disclosures by private firms are associated with decreased investor holdings of public firm equity, indicating a negative spillover effect on public firms in capital markets as private firms become more transparent. Similarly, Beyer, Flagmeier, and Kosi (2024), analyzing U.S. firms for the year 2018, observe that across various industries, analysts' earnings forecast accuracy for public firms is negatively related to the prominence of private firms within an industry. The authors interpret this as private firm disclosures generating negative externalities. Conversely, Chen, Ng, Saffar, and Yang (2023) find that increased private firm disclosures reduce public firms' borrowing costs, especially when bank oversight is weak and the public firm is opaque, suggesting that private disclosures can produce positive information spillovers. Our study indicates that multiple forces operate simultaneously: on one hand, improved dissemination of private firm information expands analysts' information sets, thereby enhancing their forecast accuracy; on the other hand, the reallocation of capital resources from public to private firms diminishes analysts' incentives to cover public firms, which reduces forecast accuracy. These opposing effects collectively influence the overall externalities of private firm information on analyst forecasts. This perspective helps reconcile the seemingly conflicting findings reported in previous research.

Our study also sheds light on how financial analysts utilize peer firm information to formulate earnings forecasts. Brown, Byard, Darrough, and Suh (2024) demonstrate that the delisting of public firms due to mergers and acquisitions (M&As) has negative externalities on the analyst forecasts of peer firms, highlighting the importance of peer

[6] Relatedly, studies have explored the information spillovers from public firm disclosures including Badertscher et al. (2013) and Shroff et al. (2017), but they do not consider the impact on analyst forecasts.

public firm information in analyst decision-making. We complement their findings by showing that private peer firm information is relevant for analyst earnings forecasts. Three distinctive features of our setting are noteworthy. First, while M&As are firm-level decisions driven by market conditions and firm incentives, our study focuses on a regulatory event, which has different implications for regulators and information users. Second, because a large number of firms are simultaneously subject to this regulatory requirement, our setting allows us to identify which peer firms are most relevant for analyst decisions. Third, as explained, our setting enables us to explore not only the direct effect from information spillovers but also the indirect effect arising from resource reallocation. Our evidence suggests that analysts particularly focus on the focal firm's suppliers, customers, and competitors. The study deepens our understanding of how analysts use input information to generate output such as earnings forecasts, an area that warrants further research attention (Schipper 1991; Brown 1993; Ramnath, Rock, and Shane 2008; Bradshaw 2011).

2. Related Literature and Hypothesis Development

2.1 Analysts' Use of Information

Traditionally, analysts relied on public financial statements, management disclosures, and industry data as input information (Helfin, Kross and Suk 2012). Recent research reveals a more nuanced and evolving landscape in which analysts integrate diverse information sources to enhance forecast accuracy and influence market outcomes. Guan, Wong, and Zhang (2015) show that analysts who cover a (supplier) firm along with its major customer benefit from informational complementarities, enabling them to generate more accurate earnings forecasts for the firm compared with scenarios where analysts do not also cover a firm's major customers. The improved accuracy is particularly pronounced following customer firms' earnings announcements, suggesting the importance of understanding a firm's supply-chain activities when forecasting its earnings (Guan et al. 2015). Luo and Nagarajan (2015) further find that analysts strategically specialize in supply chain relationships especially when there is a high information complementarity.

Analysts also utilize organizational resources within their brokerage houses. Huang, Lin, and Zang (2022) document that analysts whose colleagues cover economically connected industries exhibit superior forecast accuracy. This suggests that informal information sharing among colleagues, facilitated by co-location and collaborative incentives, enhances analysts' understanding of industry dynamics and firm fundamentals.

Going beyond traditional sources, some analysts seek non-public information through regulatory channels. Klein, Li, and Zhang (2020) examine how healthcare analysts use the Freedom of Information Act to obtain records from the U.S. Food and Drug Administration, such as factory inspection reports and drug approval documents. Gibbons, Iliev, and Kalodimos (2021) track analysts' access to the SEC's EDGAR database and find that analysts who review filings before issuing forecasts produce more accurate earnings estimates and provide forecasts for a greater number of metrics and time horizons, indicating deeper engagement with firm fundamentals. The use of EDGAR is driven by both external demand (e.g., investor interest in large or volatile firms) and internal incentives (e.g., career concerns and prior forecast errors).

Analysts also assimilate information from the financial press. Bradshaw, Lock, Wang, and Zhou (2021) show that firm-specific news coverage triggers analyst revisions and amplifies market reactions to those revisions. Their study finds that analysts who cite media sources in their reports are more likely to revise recommendations and that these revisions elicit stronger price responses. This suggests that analysts serve as interpreters of qualitative signals, translating them into actionable investment advice. Finally, the rise of big data adds new dimensions to analyst research, enabling analysts to tap into more extensive data sources (Chi, Hwang, and Zheng 2025).

2.2 Analyst Earnings Forecast Accuracy

The availability of high-quality information is of fundamental importance for analyst forecast accuracy. Hope (2003) finds that firm-level annual report disclosures are positively associated with forecast accuracy across 22 countries because detailed disclosures about accounting policies, segment performance, and strategic plans help reduce uncertainty and improve analysts' understanding of firm fundamentals. Moreover, the impact of disclosure is more pronounced where public reports serve as the primary information source.

Because information about one firm has implications for other firms in the same industry (e.g., Foster 1981, Baginski 1987, Han, Wild and Ramesh 1989; and Kim, Lacina and Park 2008), analysts often exploit intra-industry information spillovers to refine their forecasts (Hilary and Shen 2013). At the same time, however, analysts appear unable to fully utilize such information spillovers and tend to underreact (Ramnath 2002). Hinson and Piao (2025) show that when a public firm goes private and exits the SEC reporting regime, analysts' forecasts for its peers become less accurate and are more dispersed, reflecting a deterioration in the information environment. Brown et al. (2024) provide similar evidence in the context of public firm's delisting resulting from M&A transactions.

Private communication with management also provides valuable input for analysts. Analysts frequently engage in private calls and meetings to validate assumptions and gain qualitative insights, especially in the pre-Regulation Fair Disclosure era (Helfin, Kross and Suk 2012). In a shifting trend toward data science and technological sophistication, analysts increasingly leverage alternative data such as satellite imagery, web traffic, and sentiment analysis, into their reports to produce more accurate earnings forecasts (Chi, Hwang, and Zheng 2025).

2.3 Hypothesis Development

Understanding the industry environment is crucial for business forecasting, with some even considering industry knowledge to be "the single most useful input to analysts' earnings forecasts and stock recommendations" (Brown, Call, Clement and Sharp 2015, p.41). Consistent with this view, research finds that analysts use public peer firms' disclosures in their decisions (e.g., Boni and Womack 2006; De Franco, Hope and Larocque 2015; Han, Hu, Huang and Xue 2021; Brown, Byard, Darrough and Suh 2024).

Most firms globally are private (unlisted), and they account for over half of total sales. Given their economic significance, it is essential to include private firms to gain a comprehensive understanding of industry conditions. However, private firms tend to be small on an individual basis. As such, their disclosures may primarily contain idiosyncratic information (Bushman, Piotroski, and Smith 2004; Breuer, Hombach, and Muller 2020), providing limited insights into broader industry-wide trends. Even if disclosures from private firms are valuable for analysts, the cost of acquiring and aggregating information across numerous private entities is considerable (Bourveau, Garel, Joos and Petit-Romec 2022; Jiao 2023), which hampers their practical utilization. In our setting, the implementation of EBRs enhances the accessibility of private firm information, allowing analysts to retrieve and analyze data more efficiently. With access to information covering a broader set of firms, analysts can better discern industry trends and opportunities, thereby enhancing their ability to forecast firms' future performance. In other words, positive spillovers from improved information dissemination should lead to increased accuracy in analyst forecasts for public companies, the direct effect of private firm information dissemination.

However, beyond this direct effect, we also anticipate changes in analyst incentives to cover public firms, which results from the reallocation of resources between private and public firms. Theoretical studies have highlighted negative spillovers of increased public disclosure. For instance, when investors have limited capacity to process information (Fishman and Hagerty 1989) or when capital supply in an economy is scarce (Zhang 2013), increased disclosure by some firms can divert resources away from others. Empirical evidence supporting these predictions has been reported by Kim and Olbert (2022) and Liu, Shi, Zeng, and Zhang (2023).[7] In our context, the enhanced dissemination of private firm information increases investors' interest in private firms, thereby diverting capital away from public firms. This shift in capital allocation reduces the demand for financial analysis of public firms, which in turn diminishes analysts' incentives to produce accurate earnings forecasts, causing the indirect effect.

With these opposing forces at work, it is ex-ante unclear which force dominates in determining how private firms' information influences analyst forecasts for public firms.[8] Our hypothesis below is stated in the null form:

H1: *Analysts' public firm earnings forecast accuracy is not related to improved dissemination of private firms' financial information.*

[7] Duguay, Minnis, and Sutherland (2020) also show a crowding out effect in the context of auditing regulation.

[8] For example, in Zhang's (2013) theoretical model, the (positive) direct effect can potentially be outweighed by the (negative) indirect effect as the quality of financial reporting standards improves.

3. Research Design

3.1 Empirical Models

We perform DiD tests around the implementation of centralized EBRs across Europe. Due to the different legislation processes of individual EU countries, the actual implementation dates of Directive 2003/58/EC vary across countries, and such differences are likely exogenous to private firms' disclosure decisions (Breuer and Breuer 2022; Kim and Olbert 2022). As EBRs are not implemented outside the EU, we use non-EU countries as a control group. Table 1 lists the countries in the treatment (EU) and control (non-EU) groups, together with the years in which EU countries implemented EBRs—which range from 1999 to 2018. The staggered nature of EBR adoption alleviates the concern of concurrent events confounding our tests.

[Table 1 about here]

We use the following basic regression model to test how the improved dissemination of private firm information affects analyst forecast accuracy for public firms:

$$Ferror = \alpha + \beta_1\, Post\_BR + \Gamma * Controls + Firm\ FEs + Year\ FEs + \varepsilon. \qquad (1)$$

In Eq. (1), *Ferror* is our measure of analysts' earnings forecast errors (the inverse of forecast accuracy). For each public firm-year, *Ferror* is calculated as the natural logarithm of the absolute value of the average forecast error across individual analysts following the firm in the fiscal year, where the forecast error of each individual analyst equals the absolute difference between the actual EPS and the forecast EPS, scaled by the absolute actual EPS. We restrict individual forecasts to those issued during the first 11 months of the fiscal year (Clement 1999).[9] *Post_BR* is an indicator variable whose

[9] According to Clement (1999, p.292), "An analyst who only releases forecasts more than 12 months prior to period end is not likely to be following companies very closely. Similarly, an analyst who only releases forecasts less than 30 days prior to period end is more likely to be mimicking the forecasts of other analysts

value is set to one for years after the EBR starts operating in a firm's country and zero otherwise.[10] Its coefficient captures the change in analyst forecast errors for the treated group post versus pre EBR adoption, benchmarked against the control group.

Following Dhaliwal, Radhakrishnan, Tsang and Yang (2012), we include in Eq. (1) a vector of controls known to be correlated with analyst forecast accuracy. They are: *ROA*, equal to profit after tax in year *t* divided by total assets in year *t*; *MTB*, equal to market capitalization divided by the book value of equity at the beginning of year *t*; *Size*, equal to the natural logarithm of total assets in year *t; Loss*, an indicator variable equal to one if profit after tax is negative in year *t* and zero otherwise; *Anano*, equal to the natural logarithm of the total number of unique analysts covering the firm in year *t*; *Horizon*, equal to the natural logarithm of the average analyst forecast horizon (the length of time between the forecasting date and the earnings announcement date) in year *t; Sdeps*, the natural logarithm of the time-series standard deviation of earnings per share calculated over the ten years prior to year *t*; *FFIN*, an indicator variable equal to one if a firm's scaled accruals in year *t* are above the country-industry-year mean and zero otherwise; *Stk_Exch*, a score summarizing all the major stock exchanges on which a firm was listed in year *t*; and *IFRS*, an indicator equal to one if the firm has adopted IFRS reporting in year *t*, and zero otherwise. Appendix A presents variable definitions.

We further include firm and year fixed effects to control for time-invariant firm characteristics and time trends. By including these fixed effects, we essentially perform a within-firm and within-year analysis. Standard errors are clustered at the country-year level.

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rather than following the companies himself." Nonetheless, our results are not sensitive to this sample restriction.

[10] We include the event year in the definition of *Post_BR*. Our inferences are unchanged if we exclude the event year from the analyses.

3.2 Sample and the Descriptive Statistics

Our sample is at the intersection of I/B/E/S, Compustat Global, and Orbis. We retrieve analyst forecast data from I/B/E/S Detail History. We restrict the sample to forecasts made at least 30 days, but not more than one year, before the end of the fiscal year (so the minimum forecast horizon is 30 days). To mitigate the impact of extreme individual analyst forecast errors, we truncate individual analyst forecast errors at the 1% level.[11] We obtain public firms' financial and stock price data from Compustat Global.

We retrieve private firm data from the Bureau van Dijk Orbis database which covers public and private firms worldwide. For inclusion in our sample, we require observations: (i) to come from non-financial industries, (ii) to have data available for all variables in Eq. (1), (iii) to come from an industry with private firms covered by the Orbis database, and (iv) to come from a country with at least 100 public firm-year observations in the final sample. We set the sample period from 2000 to 2019 because (i) the Orbis coverage of private firms becomes comprehensive from early 2000s and (ii) we intend to exclude the covid-19 pandemic years from our analyses. This selection procedure yields a final sample of 113,684 public firm-year observations; see Table 2 for details.

[Table 2 about here]

Panel A of Table 3 presents the sample distribution by industry. Among the 17 industries based on NACE industry classification, Manufacturing has the largest representation (53.62% of the sample), followed by Information and Communication (10.98%) and Wholesale and Retail Trade & Repair of Motor Vehicles and Motorcycles (10.58%). At the other extreme, industries with the lowest representations are Public

[11] Our inferences remain the same without the truncation.

Administration and Defense & Compulsory Social Security (0.03%), Education (0.25%), and Other Service Activities (0.26%).

[Table 3 about here]

Panel B of Table 3 presents the descriptive statistics of our variables. The dependent variable *Ferror* has a mean value of -1.429. For private firms, the mean value of *Post_BR* is 0.193. For public firms, the mean *ROA* is 0.032, and the mean market-to-book ratio (*MTB*) is 2.375. The logarithm of total assets (*Size*) has a mean of 6.003, and the mean probability of incurring a loss (*Loss*) is 15.9%. On average, the logarithm of analyst coverage (*Anano*) is 1.372, the logarithm of forecast horizon (*Horizon*) is 5.432, and the logarithm of earnings volatility (*Sdeps*) is 1.292. The mean likelihood of firms having high scaled accruals (*FFIN*) is 25.4%, and that of firms having adopted mandatory IFRS reporting (*IFRS*) is 40.5%. The mean score for a firm's listing on various stock exchanges (*Stk_Exch*) is 0.273.

Panel C reports the pair-wise Pearson correlations between the variables. Analysts' public firm earnings forecast error (*Ferror*) is significantly negatively correlated with the indicator for the information dissemination shock (*Post_BR*) (corr. = -0.053, $p < 0.01$). This preliminary evidence suggests that private firm information dissemination is associated with more accurate analyst earnings forecasts for peer public firms.

4. Main Results

4.1 Staggered Difference-in-Differences Regressions

Panel A in Table 4 presents the test results for Eq. (1). The coefficient on *Post_BR* is negative and significant (-0.231, t = -4.70), indicating that increased financial information dissemination through EBR adoption significantly improves analysts' forecast accuracy. This result translates to an average reduction in forecast errors of 20.6% (= $e^{-0.231}$-1).

[Table 4 about here]

Panel B in Table 4 provides the results of testing the parallel trend assumption, where we use year *t-1* (the year immediately preceding the EBR implementation) as the base year. The pre-event differential effects on the treated, versus the control, group are all mild and statistically insignificant. In contrast, the differential analyst forecast errors are significantly negative throughout the post-event period. This result supports the parallel trend assumption. Figure 1 maps out the differential effects on analyst forecast errors across the years surrounding the EBR implementation.

[Figure 1 about here]

4.2 Sensitivity Checks

To check the robustness of our results, we repeat the above analysis (i) using alternative samples, (ii) including alternative fixed effect structures, (iii) adopting alternative ways to cluster standard errors, and (iv) controlling for additional country-industry-year level characteristics in our regressions. In addition, we explore whether the dissemination effect is dependent on the level of private firm information disclosure. The results are reported in Table 5.

In Panel A of Table 5, we restrict the sample to EU countries given that EBRs are required only in the EU. We also adjust our sample to exclude the years of the dot-com bubble in early 2000s, the 2008 financial crisis, or both, since these two periods overlap with the years of adopting business registers in certain EU countries. We construct five alternative samples that represent various combinations of these adjustments. As shown in columns (1) through (5), the coefficient on *Post_BR* is significantly negative across all samples.

Panel B of Table 5 reports the results of using alternative fixed effect structures. In column (1), we control for country-industry and year fixed effects and obtain a significant negative coefficient on *Post_BR* (-0.220, t = -5.00). In column (2), we control for country-industry and industry-year fixed effects and obtain a similar coefficient (-0.186, t = -4.68). In column (3), we control for country, industry, and year fixed effects, and continue to observe consistent results (-0.209, t = -4.88).

[Table 5 about here]

Panel C of Table 5 shows the results under alternative ways of clustering standard errors, ranging from the least strict (i.e., at firm level) to the strictest (at country and year levels). Across all specifications, the coefficient on *Post_BR* remains negative and significant at the 5% level or better.

Panel D of Table 5 shows the results after controlling for a series of country-industry-year level factors that could affect analyst forecast accuracy. Following Kim and Olbert (2022), we include in Eq. (1) public firm disclosure transparency (*Dislcosure_Pub*), private firm presence (*Pres_Priv*), aggregate size of private firms (*Size_Priv)*, median size of private firms (*MedianSize_Priv*), median size of public firms (*MedianSize_Pub*), average ROA of private firms (*ROA_Priv*), average ROA of public firm (*ROA_Pub*), and aggregate revenue size of industry (*Revenue_All*). We continue to obtain significantly negative coefficient on *Post_BR* (-0.217, t = -4.30), indicating that the effect of the private firm information dissemination shock is incremental to these industry-year level characteristics.

Panel E shows that the effect of information dissemination hinges on the level of private firm disclosures. The Orbis database records up to 39 financial statement line items that private firms disclose under the various regulations they are subject to.[12] To measure private firms' financial disclosure level, we follow a two-step procedure adopted by prior studies (Kim and Olbert, 2022; Chen, Miao and Shevlin, 2015). We

[12] See Appendix B for details of the 39 line items.

first calculate the firm-level disclosure intensity, whose value ranges from 1/39 (the lowest disclosure level) to one (the highest). We then calculate the mean value of firm-level disclosure intensity for firms operating in a specific (three-digit NACE) industry and multiply it by the number of disclosing private firms in the country-industry-year. As a result, we obtain a country-industry-year level measure for private firm financial disclosure level, which is based on the total number of non-missing private firm financial statement line items aggregated at the country-industry-year. In our regressions, we use the standardized disclosure level (*Disclosure*) which has a mean value of zero and a standard deviation of one. If the effect of improved information dissemination increases with the level of private firms' disclosure, the coefficient on *Post_BR*Disclosure* will be significantly negative.

Figure 2 presents private firm disclosure levels by industry. The industries with the highest amounts of private firm disclosure are Construction (*Disclosure* = 11.05), Professional, Scientific and Technical Activities (10.14), and Other Service Activities (10.06). On the other hand, Public Administration and Defense & Compulsory Social Security (4.82), Mining and Quarrying (6.60), and Agriculture, Forestry and Fishing (6.91) have the lowest private firm disclosure levels.

[Figure 2 about here]

As shown in Panel E of Table 5, the coefficient on *Post_BR * Disclosure* is negative and significant (-0.134, t = -4.49), indicating that the effect of information dissemination is stronger in industries where private firms disclose more information.[13] Meanwhile, the coefficient on *Disclosure* itself is insignificant. These results suggest

[13] In further analysis we break the disclosure measure *Disclosure* into three component measures, denoted as *Disclosure_BS* (for balance sheet), *Disclosure_IS* (for income statement), and *Disclosure_FN* (for footnotes). Untabulated results show that the interactions between the component measures and Post_BR all have a significant negative coefficient; thus, information dissemination helps to reduce analysts' public firm earnings forecast errors irrespective of whether it is balance-sheet information, income-statement information, or footnote information.

that the effect of information dissemination is conditional on how extensively firms disclose information. Beyond its effect that goes through improved information dissemination, the level of private firm disclosure per se displays no additional effect in explaining the changes in forecast errors.

4.3 Stacked Difference-in-Differences Model Using Alternative Samples

Staggered DiD results can be biased due to treatment effect heterogeneity (Baker, Larcker, and Wang 2022). To address this concern, we now adopt stacked DiD models using several more refined samples to further validate our findings (Cengiz, Dube, Lindner, and Zipper 2019). Specifically, we create a cleaner cohort for each EBR implementation using an event window of [-3, +2] years. These event-specific cohorts are then put together to form a stacked sample. We re-estimate the DiD regression using cohort-specific fixed effects for (i) the full sample, (ii) a balanced sample, and (iii) a constant firm-analyst sample.

Panel A of Table 6 reports the regression results. Column (1) presents the stacked DiD results for the full sample. The coefficient on *Post_BR* is significant and negative (-0.310, t = -3.50), which confirms the results from the staggered DiD tests. For most countries in our sample, the number of observations is unbalanced pre versus post EBR implementation. To mitigate this issue, we construct a balanced sample with constant firms over the period of [-3, +2] years. That is, we drop those firms that enter or exit our sample during this period. As shown in column (2), the coefficient on *Post_BR* is again significantly negative (-0.398, t = -3.52).

To address the possibility that our results are driven by changes in firm-analyst pairs around the EBR implementation, we re-estimate our stacked DiD regression model using a sample of constant firm-analyst pairs over the period of years [-3, +2].[14] We

[14] We use individual analyst-level forecast errors to run this regression so that we have the same analyst

require a balanced sample with at least one firm-analyst observations in both pre- and post-periods. Column (3) shows that the coefficient on *POST_BR* remains significantly negative (-0.252, t = -3.02). This alleviates the concern of analyst selection changes.

[Table 6 about here]

Panel B of Table 6 reports the parallel trend analyses for the three stacked DiD samples. The results indicate that the differential effects on analyst forecast errors are insignificant in the pre-event period and exhibit a sharp decline immediately following the EBR implementation.

5. Exploring How Analysts Utilize Private Firm Information

In this section, we conduct cross-sectional analyses to identify which types of private firms are most relevant when analysts utilize private firm information. Additionally, we explore whether the impact of private firm information varies with the timeliness of private firm disclosures.

5.1 Private Firms as Reference Points

When extracting relevant information from private firm disclosures, analysts are likely to focus particularly on certain private firms—either because they have direct business relationships with the focal public firm (namely, its suppliers and customers) or because they closely compete with the focal public firm. We identify three types of such firms: the focal firm's suppliers, customers, and competitors. In each case, the financial information of private firms can be particularly useful for forecasting the focal firm's performance. Thus, we expect that the benefit of having private firm information is greater in the presence of these private firms as reference points.

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following the same firm over the sample period.

We identify public firms' exposure to these types of private firms using the FactSet Revere database, which provides public firms' self-reported information on related business entities including customers, suppliers and competitors. We then determine which of these related business entities are private firms. Panel A in Table 7 reports the results when the focal public firm is exposed to a private customer firm, whereby we set the indicator variable *Priv_Exposure* to one for public firms having at least one private firm customer and zero otherwise. We expand the regression specification in Eq. (1) by including *Priv_Exposure* and its interaction with *Post_BR*. We restrict the search for private firm customers to private firms from EBR adopting countries in column (1) and private firms from the same country as the focal public firm in column (2). The coefficient on *Post_BR* is significantly negative in both specifications, confirming our baseline results. Importantly, the coefficient on *Post_BR*Priv_Exposure* is also significantly negative, suggesting that the effect of EBR implementation on analyst forecast accuracy is more pronounced for public firms that sell to private firm customers.

[Table 7 about here]

Panel B reports the results for the scenario when the focal public firm is exposed to private firm suppliers, where we set the indicator variable, *Priv_Exposure*, to one for public firms having at least one private firm supplier and zero otherwise. We restrict the search for supplier firms respectively to private firms from EBR adopting countries in column (1) and domestic private firm suppliers in column (2). The coefficient on *Post_BR*Priv_Exposure* is negative in both columns and is significant in column (1). This suggests that the effect of private firm information around EBR adoption is stronger where public firms rely on private firms for supplies.

Finally, we consider the scenario where the focal public firm is directly competing with private firms within the same industry. In this case, we set *Priv_Exposure* to equal one for public firms having at least one private firm competitor, and zero otherwise. Panel C of Table 7 reports the results, where competitors are private firms from EBR adopting countries in column (1) and domestic private firms in column (2). In both columns (1) and (2), the coefficient on *Post_BR*Priv_Exposure* is negative and significant, consistent with the notion that financial information about private firm competitors provides useful performance benchmarks to analysts, increasing their ability to make accurate earnings forecasts for the focal public firm. Taken together, the results in this subsection shed light on how analysts use private firm information to improve their public firm forecasts.

5.2 Varying Treatment Effects Attributed to the Timing of Private Firm Disclosures

To strengthen the connection between EBR implementation and analyst forecast accuracy, we now investigate how the effect of private firm information varies with the timing of private firm disclosures. We conduct two analyses for this purpose.

The first analysis focuses on the initial year of EBR implementation. We divide the year into the first and second half-years and expect the impact of EBR implementation to be more pronounced in the second half of the year because private firms are more likely to have filed their disclosures by then. Accordingly, we use two indicator variables *Year-0-1st Half* and *Year-0-2nd Half* for the two half-years and run a dynamic model. Table 8, Panel A, shows that the coefficient on *Year-0-1st Half* is negative but insignificant (-0.095, t = -1.51), and that on *Year-0-2nd Half* is significantly negative (-0.132, t = -2.77), consistent with the view that analysts can better benefit from private firm information later in the year when more private firms have disclosed their information.

[Table 8 about here]

In our second analysis, we posit that private firm information is most useful the earlier it is disclosed in the focal public firm financial year, since it provides timely information about the economic environment in which the public firm is operating. To test this conjecture, we compare analyst forecasts issued for public firms with high versus low timing overlap, where timing overlap refers to the period from the private firm disclosure date (for financial year *t-1*) to the focal public firm's financial year end (year *t*).

For this analysis, we identify the country-industry-year level private peer firm disclosure date using two factors: (1) the common fiscal year end of the majority of private firms from a given country-industry-year, and (2) the disclosing deadline enforced by different EU member states (see Appendix D). The private firm disclosure date, by which most private firms in the industry are expected to have disclosed their financial information, is estimated as (1) + (2). Disclosure timing overlap measures the number of months during which the period following private firm disclosures overlaps with the focal public firm's fiscal year. The overlap duration ranges from 0, indicating that the latest year's private firm information is *not* available at all during the fiscal year of the focal public firm, to 12 months, meaning that the latest private firm information is available throughout the entire fiscal year of the focal public firm. Figure 3 provides an illustrative explanation of the disclosure timing overlap.

We include in our baseline specification the variable *High_Timing_Overlap* that equals 1 if the timing overlap length is higher than the country-specific median, and 0 otherwise, and its interaction with *Post_EBR* to capture the incremental effect of more timely private firm disclosures on the relationship between improved private firm information dissemination and analyst public firm forecast accuracy. Our expectation is that analysts benefit more from private firm disclosures that are made available earlier in the public firm's financial year.

[Figure 3 about here]

Panel B of Table 8 presents the results of this analysis. While the coefficient on *Post_BR* (-.185, t = -3.94) is negative and significant suggesting all public firms irrespective of private firm information disclosure timing benefit from improved dissemination of private firm information, the negative and significant coefficient on the interaction term *Post_BR*High_Timing_Overlap* (-0.109, t = -2.83) suggests that analyst forecast accuracy is greater for public firms with greater timing overlap with peer private firms. Taken together, these results demonstrate that while the implementation of EBRs has generally improved analyst forecast accuracy, this effect is stronger in situations where the latest year's private firm information is made available to analysts in a timelier manner.

6. Indirect Effect through Analyst Incentives

Next, we examine whether changes in analyst incentives, induced by resource reallocation from public to private markets, influence the effects of EBR implementation on analyst public firm forecasts. As previously discussed, this indirect effect countervails the direct information effect. We seek evidence of the indirect effect on two levels. First, we explore the shifting of capital from public to private firms around the implementation of EBRs and link this shift to analyst forecast accuracy. Second, we examine changes in financing activities for public firms around the EBR implementation, and the related impact on analyst incentives to cover public firms, and link the treatment effect to these changes.

6.1 Shifting Private Equity Investments from Public to Private Firms

As private firms' information dissemination improves, capital is diverted away from public firms to private firms. The capital reallocation reduces the demand for analyst services in the public market, leading to diminished analyst incentives to improve forecast accuracy. To test this conjecture, we utilize private equity (PE) investment information from the Orbis M&A database (formerly Zephyr) and measure capital reallocation by either (i) assets involved in PE deals (*PE_Assets*) or (ii) equity value involved in PE deals (*PE_Equity*) for both public and private firms.

Panel A in Table 9 reports the results based on *PE_Assets*. We obtain a significantly positive coefficient on *Post_BR* for private firms in column (1), and a significantly negative coefficient on *Post_BR* for public firms in column (2). These results suggest that the implementation of EBR is associated with PE investments shifting away from public firms and into private firms. Panel B in Table 9 reports similar results when we use *PE_Equity*. These results show that the findings of Kim and Olbert (2022) also hold in our sample.

Next, we link the shift in PE investments to analyst forecasts. Specifically, we define a variable (*PE_Priv_Increase*), which takes the value of one if a country-industry-year experienced an increase in PE investments in private firms around the adoption of EBR, and zero otherwise, and include this variable together with its interaction with *Post_BR* in Eq. (1). As shown in Panel C of Table 9, we obtain a positive and significant coefficient on the interaction term *Post_BR*PE_Priv_Increase,* irrespective of whether PE investments are measured by equity or assets. While the coefficient magnitude is smaller than that for *Post_BR*, these results suggest that where resources are reallocated to private firms, the benefit of EBR implementation on analysts' public firm forecast accuracy is diminished.

[Table 9 about here]

6.2 Changes in Public-Market and Analyst Activities around EBR Adoption

In this subsection, we seek further evidence on the indirect effect by examining (i) financing and trading activities in public markets, (ii) the linkage of these market activities to analysts' incentives to cover public firms, and (iii) the linkage of analyst incentives to their forecast accuracy.

First, we examine changes in public firms' financing activities and stock trading volumes, which are factors driving the demand for analyst services. We measure (i) public firm financing (*Financing*), as the net change in equity stock less purchase of treasury shares plus change in long term debt for year *t*, divided by total assets for year *t-1*, and (ii) stock trading volume (*Trading Volume*), as the natural log of the number of shares traded in year *t*. The results are presented in Panel A of Table 10. We find a negative and significant coefficient on *Post_EBR* in explaining either *Financing* or *Trading Volume*, suggesting a reduction in public firms' financing activities and the trading volume of their stocks following the EBR implementation. This result is consistent with the presence of a crowding out effect on public firms post EBR.

Next, we link the changes in financing and trading activities to analysts' interest in covering public firms: (i) analyst following (*#Analysts*) and (ii) the number of forecast issuances (*#Forecasts*). We partition observations into terciles on the change in financing activities and use *Drop1_Fin* and *Drop2_Fin* to respectively indicate those in the medium- and largest-drop terciles, versus the smallest or no drops, in financing activities. Similarly, we use *Drop1_Vol* and *Drop2_Vol* to indicate observations in the medium and largest-drop terciles in trading volume, respectively.

Panel B of Table 10 shows the results for this analysis. Specifically, the coefficients on *Drop1_Fin* and *Drop2_Fin* are significant and negative both in explaining *#Analysts* and *#Forecasts*. Also, the coefficients on *Drop1_Vol* and *Drop2_Vol* are negative and generally significant in explaining *#Analysts* and *#Forecasts*. That is, public firms experiencing significant reductions in financing activities and trading volumes following the implementation of EBR experience correspondingly larger drops in analyst following and forecast issuances, which supports the view that analyst incentives are linked to financing and trading activities.

[Table 10 about here]

Lastly, we link reduced analyst incentives to forecast accuracy. To do so, we first calculate the changes in *#Analysts* and *#Forecasts* around the EBR implementation over the window of (-3, 3) years. We split these changes into terciles and use *Dec1_#Analysts* and *Dec1_#Foercasts* to indicate observations in the middle tercile, and *Dec2_#Analysts* and *Dec2_#Forecasts* to indicate observations in the tercile with the largest decreases. We include these variables and their interactions with *Post_BR* in Eq. 1 to explain forecast errors. The results are reported in Panel C of Table 10. First, the coefficient on *Post_BR* is significantly negative in both columns in the panel, indicating a general improvement in forecast accuracy. However, the coefficients on *Post_BR*Dec1_#Analysts* and *Post_BR*Dec2_#Analysts* are positive and significant, but their magnitudes are smaller than on those for *Post_BR*, indicating a (partially) offsetting effect that attenuates the improvement in forecast accuracy. We obtain similar inferences when using changes in forecast issuances, although the statistical significance of the results is weaker. Overall, with the results in Panels A to C, we establish the link from the crowding out of public firms around the EBR adoption, to diminished analyst incentives, and finally to relatively low forecast accuracy.

7. Are the Results Driven by Changes in Firms' Disclosure Levels?

In this section, we conduct analyses to address the concern that our results are driven by changes in firms' disclosure levels. While Directive 2003/58/EC itself does not introduce changes in the level of financial information disclosures, it is possible that private firms and/or their public peers adjust their disclosure levels. If this is the case, the documented effect in terms of reduced forecast errors could result from increased disclosures by either private or public firms, rather than improved information dissemination. To address this concern, we separately examine changes in analyst forecast accuracy (i) where private firms display increased, versus decreased, disclosures, and (ii) where public firms display increased, versus decreased, disclosures.

First, we explore whether our main results are driven by increased private firm disclosure levels. For this test, we use a balanced sample with constant firms over years [-3, +2]. We split the sample into two groups: (1) public firms whose private peer firms display a negative change (including zero change) in disclosure level, and (2) public firms whose private peer firms display a positive change in disclosure level. If our main finding is driven by increases in private firm disclosures, we expect to see increased analyst forecast accuracy for the positive change group, but not for the negative change group. However, in untabulated results, the coefficients on *Post_BR* load significantly negatively for both groups, indicating improved analyst forecast accuracy around the EBR adoption, irrespective of whether private firm disclosure levels have increased or decreased.

Similarly, to address the concern that our main results are driven by increases in public firm disclosures, we partition the sample based on whether public firms increase voluntary disclosures post EBR. We use the number of management earnings forecasts (retrieved from the Capital IQ key developments database) to proxy for voluntary disclosure levels (*MF*). Again, we use a balanced sample with constant firms over the years [-3, +2]. We split the sample into (1) public firms issuing fewer management forecasts after the EBR adoption and (2) public firms issuing more management forecasts. If our main finding is attributable to increases in public firm voluntary disclosure, we expect to find improved analyst forecast accuracy for the latter group but not for the former. However, untabulated results show that the coefficients on *Post_BR* load significantly negatively for both groups. Taken together, these results suggest that increased analyst forecast accuracy post EBR adoption is not driven by changes in information disclosures by either public or private firms.

8. Conclusions

While there is a sizeable literature on how public firms' financial reporting and disclosures affect peer firms in the industry, only scant work has examined the information externalities arising from private firms—firms that collectively make up a large part of an economy but generally remain relatively opaque. This study contributes to this nascent literature by exploring the externalities arising from improved dissemination of private firm information on analysts' public firm earnings forecasts.

We posit that improved dissemination of private firm information reduces the costs of accessing, processing, and aggregating private firm information. This allows analysts to better understand the external business environment when they analyze and assess public firms' prospects, thus enabling them to generate more accurate earnings forecasts. However, we also recognize that improved dissemination of private firm information would raise investors' interest in private firms and thus cause capital resources to be diverted from public to private firms. This reallocation of resources results in reduced investors' demand for analyst services, which leads to diminished analyst incentives to cover public firms and ultimately less accurate earnings forecasts. Thus, there are two separate forces at work in determining how private firm information disclosures affect analysts' public firm earnings forecasts.

Using the staggered implementation of EBRs in the EU as a shock to the dissemination of private firm information, we conduct difference-in-differences analyses and find a significant reduction in analysts' public firm forecast errors for treated firms relative to control firms. The effect is more pronounced in industries where private firms collectively disclose more information, and when analysts find more relevant reference points for analyzing the focal public firm's business.

At the same time, we find evidence suggesting that capital is indeed diverted away from public to private firms, and that the beneficial effect on analyst forecast accuracy is attenuated where the diversion of capital from public firms is more severe. Furthermore, there are significant reductions in both the analyst following of public firms and forecast issuances post EBR that are related to public firms' financing activities and investors' trading of their stocks. Moreover, in the subsamples where public firms do experience substantial decreases in analyst following and forecast issuances, the negative analyst incentive effect significantly attenuates the positive information spillover effect.

This study is among the first to explore the spillover effects arising from changes in private firm information dissemination. Our findings are relevant to financial analysts who utilize private firm disclosures in forecasting public firms' performance. They are also relevant to regulators who need to determine regulations on private firm disclosures and the ways to disseminate information.

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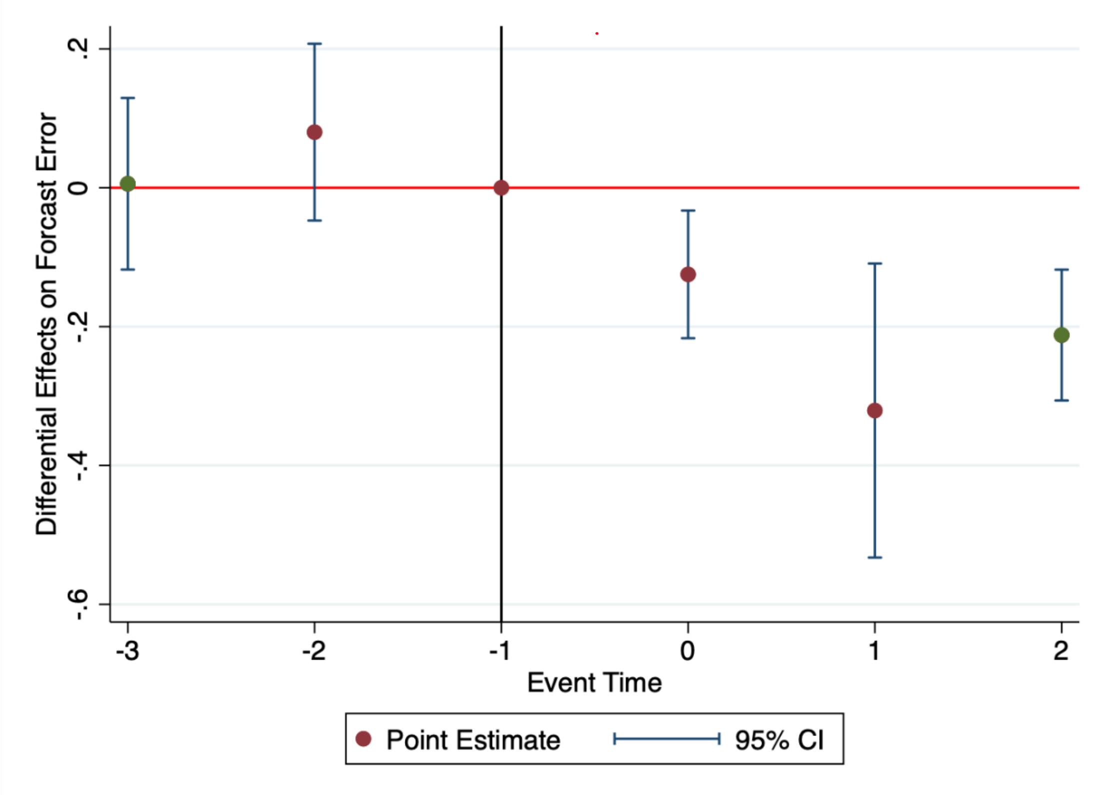
FIGURE 1

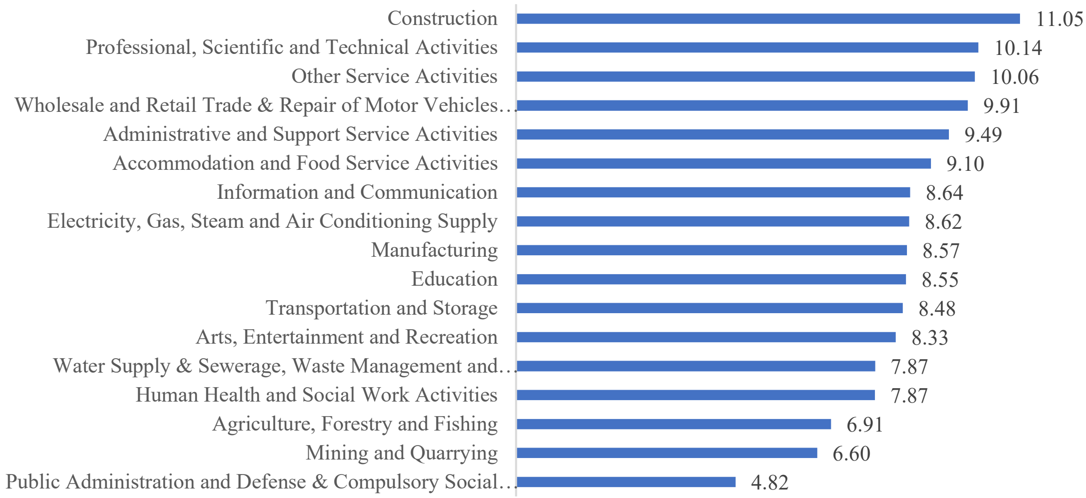
Mapping Out the Staggered Electronic Business Register Implementation Effect



This figure maps out the differential effect estimated using the EU electronic business register (EBR) implementation across the sample years, on EBR adopting countries versus non-adopting countries, using the year immediately before the EBR adoption (year -1) as the base year. Specifically, it plots the differential effects for the staggered difference-in-differences model.

FIGURE 2

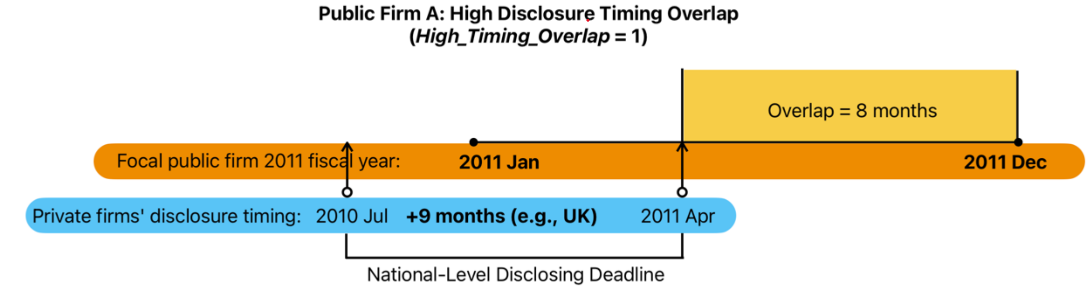
Private Firm Disclosure level by Industry

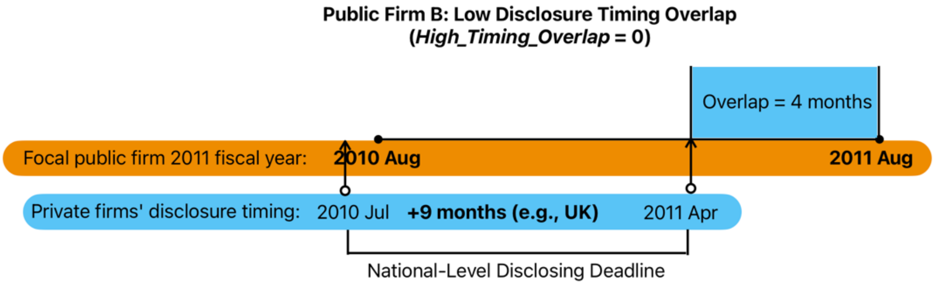


This figure presents the statistics for private firms' disclosure level across different industries. The private firm disclosure level is calculated as the mean firm-level disclosure intensity for private firms operating in the specific industry, multiplied by the number of disclosing private firms in the country-industry-year.

FIGURE 3

Illustrative Examples of Timing Overlap Between Private Firm Disclosure and the Focal Public Firm's Fiscal Year





This figure demonstrates two illustrative scenarios, where the blue timeline represents the disclosure timing for private peer firms in the country-industry-year and the orange timeline represents the fiscal year for the focal public firm. The disclosure timing for private peer firms is identified using two factors: (1) the common fiscal year end of the majority of private firms from a given country-industry-year, and (2) the disclosing deadline enforced by different EU member states (see Appendix D). The private firm disclosure timing is estimated as (1) + (2), by which most private firms in the industry are expected to have disclosed their financial information. Disclosure timing overlap measures the number of months during which the period following private firm disclosure overlaps with the focal public firm's fiscal year. Public firm A (B) in the upper (lower) part has a higher (lower) overlap with private peer firm disclosures. Assuming a country-specific median overlap length of 6 months, public firm A (B) is coded as *High_Timing_Overlap* =1 (0).

TABLE 1

List of Countries and Electronic Business Register Adoption Years

Country	*Adopting Year*	*Treat/Control*
Austria	2001	Treat
Belgium	2008	Treat
Denmark	1999	Treat
Finland	2010	Treat
France	2001	Treat
Germany	2007	Treat
Greece	2011	Treat
Hungary	2009	Treat
Ireland	2004	Treat
Luxembourg	2007	Treat
Netherlands	2006	Treat
Norway	2007	Treat
Poland	2018	Treat
Portugal	2007	Treat
Spain	1999	Treat
Sweden	2000	Treat
UK	2007	Treat
Argentina	n/a	Control
Australia	n/a	Control
Brazil	n/a	Control
Chile	n/a	Control
China	n/a	Control
Egypt	n/a	Control
Hong Kong	n/a	Control
India	n/a	Control
Indonesia	n/a	Control
Israel	n/a	Control
Italy	n/a	Control
Japan	n/a	Control
Malaysia	n/a	Control
Mexico	n/a	Control
New Zealand	n/a	Control
Nigeria	n/a	Control
Pakistan	n/a	Control
Peru	n/a	Control
Philippines	n/a	Control
Russia	n/a	Control
Saudi Arabia	n/a	Control
Singapore	n/a	Control
South Africa	n/a	Control
South Korea	n/a	Control
Sri Lanka	n/a	Control
Switzerland	n/a	Control
Taiwan	n/a	Control
Thailand	n/a	Control
Turkey	n/a	Control
UAE	n/a	Control
Vietnam	n/a	Control

This table lists the countries in our sample and the years of implementing electronic business registers in different countries.

TABLE 2
Sample Selection Procedure

Sample Selection Procedures	**#Obs Dropped**	**#Obs Left**
1. Initial financial data with non -missing total assets from Compustat Global -Fundamentals Annual in 2000-2019		679,180
2. Merging with Bureau van Dijk Orbis database	58,142	615,636
3. Deleting financial firms	97,220	518,416
4. Merging with fiscal-year-end market price from Compustat Global - Security Daily	124,245	394,171
5. Merging with IBES database	239,957	154,214
6. Deleting firms with headquarters in USA, Canada or Bermuda	484	153,730
7. Deleting observations with missing data to calculate variables in baseline model	37,075	116,655
8. Deleting observations in countries with less than 100 observations	920	115,735
9. Deleting firms with only one single observation in the sample	2,051	113,684
Final Sample		**113,684**

This table describes the sample selection criteria which yield the final sample of 113,684 firm-year observations for the baseline model.

TABLE 3
Descriptive Statistics

Panel A. Sample Distribution by Industry

Code	*NACE Industry Classification*	#Obs	%Total
A	Agriculture, Forestry and Fishing	918	0.81
B	Mining and Quarrying	3,859	3.39
C	Manufacturing	60,961	53.62
D	Electricity, Gas, Steam and Air Conditioning Supply	2,944	2.59
E	Water Supply & Sewerage, Waste Management and Remediation Act.	618	0.54
F	Construction	4,406	3.88
G	Wholesale and Retail Trade & Repair of Motor Vehicles and Motorcycles	12,032	10.58
H	Transportation and Storage	4,859	4.27
I	Accommodation and Food Service Activities	1,993	1.75
J	Information and Communication	12,484	10.98
M	Professional, Scientific and Technical Activities	3,389	2.98
N	Administrative and Support Service Activities	2,700	2.38
O	Public Administration and Defence & Compulsory Social Security	37	0.03
P	Education	285	0.25
Q	Human Health and Social Work Activities	873	0.77
R	Arts, Entertainment and Recreation	1,025	0.90
S	Other Service Activities	301	0.26
Total		**113,684**	**100**

Panel B. Summary Statistics of Variables

VARIABLE	#Obs	Mean	SD	P25	Median	P75
Private Firm Disclosure						
Post_BR	113,684	0.193	0.395	0	0	0
Analyst Forecast Accuracy						
Ferror	113,684	-1.429	1.236	-2.330	-1.532	-0.564
Public Firm Characteristics						
ROA	113,684	0.032	0.096	0.012	0.037	0.071
MTB	113,684	2.375	2.578	0.882	1.542	2.817
Size	113,684	6.003	1.751	4.780	5.860	7.130
Loss	113,684	0.159	0.366	0	0	0
Anano	113,684	1.372	1.061	0.693	1.386	2.197
Horizon	113,684	5.432	0.248	5.278	5.436	5.606
Sdeps	113,684	1.292	3.109	-1.302	1.067	3.501
FFIN	113,684	0.254	0.435	0	0	1
Stk_Exch	113,684	0.273	0.631	0	0	0
IFRS	113,684	0.405	0.491	0	0	1
Partitioning Variables						
#Analysts	113,684	6.842	7.651	2	4	9
#Forecasts	113,410	19.782	29.773	3	8	24
Priv_Exposure (EBR Customers)	113,684	0.073	0.261	0	0	0
Priv_Exposure (Domestic Customers)	113,684	0.105	0.306	0	0	0
Priv_Exposure (EBR Competitors)	113,684	0.041	0.199	0	0	0
Priv_Exposure (Domestic Competitors)	113,684	0.037	0.189	0	0	0
Priv_Exposure (EBR Suppliers)	113,684	0.046	0.210	0	0	0
Priv_Exposure (Domestic Suppliers)	113,684	0.060	0.238	0	0	0
PE_Priv_Assets	115,734	14.431	9.292	0	19.219	21.294
PE_Priv_Equity	113,755	13.542	8.931	0	18.085	20.130
PE_Pub_Assets	115,734	15.334	9.690	0	20.295	22.089
PE_Pub_Equity	114,764	14.628	9.329	0	19.449	21.225

Panel C. Correlations (Baseline Sample)

	(1)	*(2)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
(1) Ferror											
(2) Post_BR	-0.053										
(4) ROA	-0.369	-0.085									
(5) MTB	-0.132	0.058	0.186								
(6) Size	-0.104	*-0.004*	0.111	-0.098							
(7) Loss	0.412	0.093	-0.657	-0.064	-0.147						
(8) Anano	-0.182	0.136	0.207	0.224	0.606	-0.151					
(9) Horizon	0.023	*0.002*	-0.034	*0.003*	-0.028	*0.005*	*0.001*				
(10) Sdeps	0.067	-0.251	-0.015	-0.167	0.049	*-0.002*	-0.144	-0.108			
(11) FFIN	0.076	-0.036	-0.073	*0.004*	-0.042	0.069	-0.063	-0.014	0.116		
(12) Stk_Exch	-0.062	0.292	0.029	0.056	0.372	**-0.005**	0.343	-0.027	-0.104	-0.032	
(13) IFRS	-0.058	0.519	0.011	0.077	0.120	0.042	0.267	*0.002*	-0.321	-0.064	0.280

This table provides the descriptive statistics. Panel A presents the sample distribution by industry for global public firms. The industry classification is based on NACE industry code: **A**-Agriculture, Forestry and Fishing, **B**-Mining and Quarrying, **C**-Manufacturing, **D**-Electricity, Gas, Steam and Air Conditioning Supply, **E**-Water Supply & Sewerage, Waste Management and Remediation Activities, **F**-Construction, **G**-Wholesale and Retail Trade & Repair of Motor Vehicles and Motorcycles, **H**-Transportation and Storage, **I**-Accommodation and Food Service Activities, **J**-Information and Communication, **M**-Professional, Scientific and Technical Activities, **N**-Administrative and Support Service Activities, **O**-Public Administration and Defense & Compulsory Social Security, **P**-Education, **Q**-Human Health and Social Work Activities, **R**-Arts, Entertainment and Recreation, **S**-Other Service Activities. Panel B reports the distributional statistics of main variables, and Panel C reports the pair-wise correlations between variables in the baseline model. All the correlations are significant at 1% level, except for those at 5% significance level (***bold and italic***), at 10% significance level (**bold**), or statistically insignificant (*italic*). All continuous variables are winsorized at the 1% and 99% percentiles. Please see Appendix A for detailed variable definitions.

TABLE 4

Staggered DiD Analysis

Panel A. DiD Regression Results

	DepVar= Ferror
Post_BR	**-0.231***** **(-4.70)**
ROA	-2.127*** (-13.17)
MTB	-0.011*** (-3.78)
Size	0.107*** (7.64)
Loss	0.711*** (28.37)
Anano	-0.075*** (-8.25)
Horizon	0.123*** (3.58)
Sdeps	0.009 (1.61)
FFIN	0.031*** (3.10)
Stk_Exch	-0.043 (-1.53)
IFRS	0.027 (0.93)
CONSTANT	-2.626*** (-13.00)
Firm FEs	Yes
Year FEs	Yes
CLUSTER	Country-Year
N	113,684
adj. R-sq	0.415

Panel B. Parallel Trend Analysis

	DepVar= Ferror
Year-3, before	**0.006** **(0.09)**
Year-2	**0.080** **(1.23)**
Year-0	**-0.125***** **(-2.66)**
Year+1	**-0.321***** **(-2.97)**
Year+2, after	**-0.212***** **(-4.42)**
CONSTANT	-2.621*** (-13.20)
Controls	Yes
Firm FEs	Yes
Year FEs	Yes
CLUSTER	Country-Year
N	113,684
adj. R-sq	0.415

This table reports the effect of EBR implementation on analyst earnings forecast errors for public firms. Panel A presents the staggered DiD results. *Post_BR* is an indicator variable equal to one for years after the EBR starts to operate in a firm's country and zero otherwise. Panel B maps out the time trend of differential analyst earnings forecasts pre- and post-EBR implementations. The dependent variable is *Ferror*, calculated as the natural logarithm of the absolute value of the difference between the average analyst forecasted earnings and the actual earnings scaled by the absolute actual earnings. Standard errors are clustered at country-year level, with t-statistics reported in parentheses beneath the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1st and 99th percentiles. Please see Appendix A for detailed variable definitions.

TABLE 5
Robustness Checks

Panel A. Alternative Samples

	DepVar=Ferror				
	(1)	(2)	(3)	(4)	(5)
	Within-EU	Remove dot-com bubble	Remove financial crisis	Remove dot-com bubble & financial crisis	Within-EU & Remove dot-com bubble & financial crisis
Post_BR	**-0.082****	**-0.235*****	**-0.268*****	**-0.273*****	**-0.097****
	(-2.18)	**(-4.74)**	**(-4.98)**	**(-5.01)**	**(-2.14)**
Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
CLUSTER	Country-Year	Country-Year	Country-Year	Country-Year	Country-Year
N	32,652	110,007	111,428	107,751	26,719
adj. R-sq	0.481	0.413	0.415	0.413	0.481

Panel B. Alternative Fixed Effect Structures

	DepVar=Ferror		
	(1)	(2)	(3)
Post_BR	**-0.220*****	**-0.186*****	**-0.209*****
	(-5.00)	**(-4.68)**	**(-4.88)**
Controls	Yes	Yes	Yes
Country-Industry FEs	Yes	Yes	No
Industry-Year	No	Yes	No
Country	No	No	Yes
Industry	No	No	Yes
Year	Yes	No	Yes
CLUSTER	Country-Year	Country-Year	Country-Year
N	113,735	115,673	115,735
adj. R-sq	0.297	0.302	0.274

Panel C. Alternative Clustering Choices

	DepVar=Ferror				
	(1)	(2)	(3)	(4)	(5)
Post_BR	**-0.231*****	**-0.231****	**-0.231****	**-0.231*****	**-0.231*****
	(-6.81)	**(-2.45)**	**(-2.41)**	**(-8.89)**	**(-4.50)**
Controls	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes
CLUSTER	Country-Industry	Country	Country, Year	Firm	Firm, Year
N	113,684	113,684	113,684	113,684	113,684
adj. R-sq	0.415	0.415	0.415	0.415	0.415

Panel D. Controlling for Country-Industry-Year Level Factors

	DepVar=Ferror
Post_BR	**-0.217*****
	(-4.30)
Disclosure_Pub	0.014
	(0.59)
Pres_Priv	0.056

	(1.47)
Size_Priv	-0.002
	(-1.50)
MedianSize_Priv	-0.001
	(-0.61)
MedianSize_Pub	0.004
	(0.43)
ROA_Priv	-0.235**
	(-2.22)
ROA_Pub	-1.744***
	(-13.84)
Revenue_All	0.015*
	(1.88)
Other Controls	Yes
Firm FEs	Yes
Year FEs	Yes
CLUSTER	Country-Year
N	113,684
adj. R-sq	0.418

Panel E. Information Dissemination Effect Through Private Firm Disclosure Levels

	DepVar= Ferror
Post_BR*Disclosure	**-0.134*** **
	(-4.49)
Post_BR	-0.165***
	(3.98)
Disclosure	0.013
	(0.87)
ROA	-2.124***
	(-13.14)
MTB	-0.012***
	(-3.83)
Size	0.106***
	(7.56)
Loss	0.711***
	(28.37)
Anano	-0.074***
	(-8.13)
Horizon	0.123***
	(3.59)
Sdeps	0.009*
	(1.68)
FFIN	0.031***
	(3.09)
Stk_Exch	-0.044
	(-1.57)
IFRS	0.029
	(1.03)
CONSTANT	-2.623***
	(-13.04)
Controls	Yes
Firm FEs	Yes
Year FEs	Yes
CLUSTER	Country-Year
N	113,684
adj. R-sq	0.416

This table reports the results of robustness checks, by using alternative samples (Panel A), alternative fixed effect structures (Panel B), and alternative standard error clustering choices (Panel C), and by controlling for additional country-industry-year level factors (Panel D). Panel E reports the results for information dissemination effect through private rim disclosure levels. It reports the staggered DiD regressions that recognize the role of standardized private firm disclosure levels (*Disclosure*). The dependent variable is *Ferror*, calculated as the natural logarithm of the absolute value of the difference between the average analyst forecasted earnings and the actual earnings scaled by the absolute actual earnings. *Post_BR* an indicator variable equal to one for years after the electronic business register starts to operate in a firm's country and zero otherwise. Standard errors are clustered at country-year level in Panels A, B, D and E, and at the other levels as described in Panel B, with t-statistics reported in parentheses beneath the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1st and 99th percentiles. Please see Appendix A for detailed variable definitions.

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TABLE 6
Stacked DiD Analysis

Panel A. Stacked DiD Models

DepVar=Ferror	*Full Sample*	*Balanced Sample*	*Constant Firm-Analyst Pairs*
	(1)	(2)	(3)
Post_BR	**-0.310*****	**-0.398*****	**-0.252*****
	(-3.50)	**(-3.52)**	**(-3.02)**
Controls	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Analyst FEs	No	No	Yes
CLUSTER	Country-Year	Country-Year	Country-Year, Analyst
N	210,531	90,930	1,369,998
adj. R-sq	0.419	0.421	0.473

Panel B. Parallel Trend Analysis

DepVar=Ferror	*Full Sample*	*Balanced Sample*	*Constant Firm-Analyst Pairs*
	(1)	(2)	(3)
Year-3	**0.178**	**0.227**	**0.136**
	(1.39)	**(1.62)**	**(1.59)**
Year-2	**0.107**	**0.089**	**0.032**
	(1.61)	**(0.92)**	**(0.05)**
Year-0	**-0.157*****	**-0.176****	**-0.118****
	(-2.67)	**(-2.25)**	**(-1.98)**
Year+1	**-0.389*****	**-0.529*****	**-0.403*****
	(-2.98)	**(-3.03)**	**(-2.77)**
Year+2	**-0.147****	**-0.183****	**-0.159***
	(-2.12)	**(-2.55)**	**(-1.88)**
Controls	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes
Analyst FEs	No	No	Yes
CLUSTER	Country-Year	Country-Year	Country-Year, Analyst
N	210,531	90,930	1,369,998
adj. R-sq	0.420	0.421	0.474

This table reports the electronic business register stacked DiD analysis. Panel A presents the results for the stacked analysis for the full (column 1), balanced (column 2), and constant firm-analyst pairs (column 3) sample analysis. Panel B presents tests for the parallel trend assumption for the full (column 1), balanced (column 2), and balanced firm-analyst pairs (column 3) sample analysis. *Ferror* is calculated as the natural logarithm of the absolute value of the difference between the average analyst forecasted earnings and the actual earnings scaled by the absolute actual earnings. *Post_BR* is an indicator variable equal to one for years after the electronic business register starts to operate in a firm's country and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. Please see Appendix A for detailed variable definitions.

TABLE 7

Public Firms' Exposure to Private Firms and Analyst Forecast Accuracy

Panel A. Private Firm Customers

DepVar=Ferror	*EBR Customers*	*Domestic Customers*
	(1)	(2)
Post_BR*Priv_Exposure	**-0.099****	**-0.103*****
	(-2.44)	**(-2.59)**
Post_BR	-0.220***	-0.219***
	(-4.42)	(-4.44)
Priv_Exposure	0.068***	0.055***
	(2.98)	(3.30)
Controls	Yes	Yes
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
CLUSTER	Country-Year	Country-Year
N	113,684	113,684
adj. R-sq	0.415	0.415

Panel B. Private Firm Suppliers

DepVar=Ferror	*EBR Suppliers*	*Domestic Suppliers*
	(1)	(2)
Post_BR*Priv_Exposure	**-0.081****	**-0.040**
	(-1.99)	**(-1.05)**
Post_BR	-0.226***	-0.228***
	(-4.53)	(-4.62)
Priv_Exposure	0.072***	0.048**
	(3.00)	(2.42)
Controls	Yes	Yes
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
CLUSTER	Country-Year	Country-Year
N	113,684	113,684
adj. R-sq	0.415	0.415

Panel C. Private Firm Competitors

DepVar=Ferror	*EBR Competitors*	*Domestic Competitors*
	(1)	(2)
Post_BR*Priv_Exposure	**-0.071***	**-0.094****
	(-1.75)	**(-2.07)**
Post_BR	-0.225***	-0.226***
	(-4.57)	(-4.59)
Priv_Exposure	0.033	0.057**
	(1.10)	(2.12)
Controls	Yes	Yes
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
CLUSTER	Country-Year	Country-Year
N	113,684	113,684
adj. R-sq	0.415	0.415

This table reports the results for how information dissemination effect varies with the public firms' exposure to private firms (*Priv_Exposure*). Panel A, B and C report the results for exposure to private peer firms based on customers, suppliers, and competitors, respectively. In each panel, column (1) is based on EBR level exposure, and column (2) for domestic exposure. The dependent variable *Ferror* is calculated as the natural logarithm of the absolute value of the difference between the average analyst forecasted earnings and the actual earnings scaled by the absolute actual earnings. *Post_BR* is an indicator variable equal to one for years after the electronic business register starts to operate in a firm's country and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. Please see Appendix A for detailed variable definitions.

TABLE 8

Varying Treatment Effects Related to Timing of Private Firm Disclosure

Panel A. Treatment Effect Split within the First Event Year

	DepVar= Ferror
Year-3, before	0.006
	(0.09)
Year-2	0.080
	(1.23)
Year-0-1st Half	**-0.095**
	(-1.51)
Year-0-2nd Half	**-0.132*** **
	(-2.77)
Year+1	**-0.321*** **
	(-2.97)
Year+2, after	**-0.212*** **
	(-4.40)
CONSTANT	-2.621***
	(-13.20)
Controls	Yes
Firm FEs	Yes
Year FEs	Yes
CLUSTER	Country-Year
N	113,684
adj. R-sq	0.415

Panel B. Disclosure Timing Overlap Between Focal Public Firms and Private Peer Firms

	DepVar= Ferror
Post_BR*High_Timing_Overlap	**-0.109*** **
	(-2.83)
Post_BR	-0.185***
	(-3.94)
High_Timing_Overlap	0.090**
	(2.20)
Controls	Yes
Firm FEs	Yes
Year FEs	Yes
CLUSTER	Country-Year
N	113,684
adj. R-sq	0.415

This table reports the results for the timing of private firm disclosures, examining how the dissemination effect depends on the private firm disclosure timing. Panel A focuses on the first event year when the EBR was initially introduced, and reports the results by splitting the first event year into two halves (January-June and July-December). Panel B reports the results for the disclosure timing overlap between private firm disclosure timing and the focal public firm's fiscal year timing. Disclosure timing overlap measures the number of months during which the period following private firm disclosures overlaps with the focal public firm's fiscal year. The overlap time length ranges from 0 to 12 months: (1) 0-month overlap means the latest private firm information is NOT available throughout the entire fiscal year of the focal public firm; (2) 12-month overlap means the latest private firm information is FULLY available throughout the entire fiscal year of the focal public firm. *High_Timing_Overlap* is an indicator variable, defined around the median overlap time length, equal to 1 if the overlap time length is higher than the country-specific median, and 0 otherwise. Private firm disclosure timing is defined according to (1) the majority fiscal year end of private peer firms within the same industry to the public firms, and (2) the private firms' disclosing deadline required by different EU countries. The dependent variable *Ferror* is calculated as the natural logarithm of the absolute value of the difference between the average analyst forecasted earnings and the actual earnings scaled by the absolute actual earnings. *Post_BR* is an indicator variable equal to one for years after the electronic business register starts to operate in a firm's country and zero otherwise. The interaction term *Post_BR*High_Timing_Overlap* captures the incremental effect of business register adoption for public firms whose fiscal years have higher overlap with private peer firm information disclosure. All continuous variables are winsorized at the 1st and 99th percentiles. Please see Appendix A for detailed variable definitions.

TABLE 9

Private Firm PE Financing and the Effect of EBR Adoption

Panel A. Effect of EBR on *PE Assets*

DepVar=PE Assets	*PE_Private Firms*	*PE_Public Firms*
	(1)	(2)
Post_BR	**2.042***	**-4.403*****
	(1.72)	**(-6.06)**
Controls	Yes	Yes
Country-Industry FEs	Yes	Yes
Industry-Year FEs	Yes	Yes
CLUSTER	Country-Year	Country-Year
N	115,734	115,734
adj. R-sq	0.610	0.602

Panel B. Effect of EBR on *PE Equity*

DepVar=PE Equity	*PE_Private Firms*	*PE_Public Firms*
	(1)	(2)
Post_BR	**2.066***	**-4.009*****
	(1.83)	**(-5.74)**
Controls	Yes	Yes
Country-Industry FEs	Yes	Yes
Industry-Year FEs	Yes	Yes
CLUSTER	Country-Year	Country-Year
N	113,755	114,764
adj. R-sq	0.605	0.606

Panel C. Private Firm PE Equity & Public Firm Forecast Accuracy

DepVar=Ferror	*PE Equity*	*PE Assets*
	(1)	(2)
Post_BR*PE_Priv_Increase	**0.348*****	**0.280****
	(2.61)	**(2.28)**
Post_BR	-0.512***	-0.487***
	(-3.29)	(-3.27)
Controls	Yes	Yes
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
CLUSTER	Country-Year	Country-Year
N	84,900	90,930
adj. R-sq	0.421	0.423

This table reports the results for potential spillover effects where EBR adoption helps increase private firm PE financing, which in turn reduces analysts' incentives and thus their earnings forecast accuracy for public firms. Panel A and B show evidence of EBR adoption leading to increased PE financing by private firms and decreased PE financing for public firms, as measured by PE assets and equity, respectively. Panel C continues to show the results for increased private firm PE financing (*PE_Priv_Increase*) leading to reduced analyst forecast accuracy for public firms. The dependent variable *Ferror* is calculated as the natural logarithm of the absolute value of the difference between the average analyst forecasted earnings and the actual earnings scaled by the absolute actual earnings. *Post_BR* is an indicator variable equal to one for years after the electronic business register starts to operate in a firm's country and zero otherwise. All continuous variables are winsorized at the 1st and 99th percentiles. Please see Appendix A for detailed variable definitions.

TABLE 10

Analyst Incentive Changes Around EBR Adoption

Panel A. EBR Adoption and Capital Market Activities

DepVar=	*Financing*	*Trading Volume*
	(1)	(2)
Post_BR	**-0.015***** **(-2.85)**	**-0.575***** **(-6.09)**
Controls	Yes	Yes
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
CLUSTER	Country-Year	Country-Year
N	93,320	91,738
adj. R-sq	0.254	0.897

Panel B. Capital Market Activities and Reduced Analyst Incentives to Cover Public Firms

DepVar=	*#Analysts*		*#Forecasts*	
	(1)	(2)	(3)	(4)
Post_BR	-0.641 (-1.32)	-0.204 (-0.52)	-3.510 (-1.15)	-5.103* (-1.65)
*Post_BR*Drop1_Fin*	**-0.987**** **(-2.32)**		**-10.465***** **(-3.74)**	
*Post_BR*Drop2_Fin*	**-1.101**** **(-2.37)**		**-8.640**** **(-2.49)**	
*Post_BR*Drop1_Vol*		**-0.491*** **(-1.94)**		**0.593** **(0.24)**
*Post_BR*Drop2_Vol*		**-0.545** **(-1.34)**		**-5.113***** **(-3.11)**
Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
CLUSTER	Country-Year	Country-Year	Country-Year	Country-Year
N	67,836	90,372	67,712	90,195
adj. R-sq	0.849	0.854	0.807	0.809

Panel C. Reduced Analyst Incentive Effects Weaken the Information Effect

DepVar=	*Ferror*	
	(1)	(2)
Post_BR	-0.514*** (-3.89)	-0.447*** (-3.74)
*Post_BR*Dec1_#Analysts*	**0.124**** **(2.33)**	
*Post_BR*Dec2_#Analysts*	**0.238***** **(2.71)**	
*Post_BR*Dec1_#Forecasts*		**0.021** **(0.31)**
*Post_BR*Dec2_#Forecasts*		**0.146**** **(2.12)**
Controls	Yes	Yes
Firm FEs	Yes	Yes
Year FEs	Yes	Yes
CLUSTER	Country-Year	Country-Year
N	90,930	90,540
adj. R-sq	0.421	0.422

This table presents the results on the indirect effect of private firm information dissemination through the resource reallocation channel that diminishes analyst incentives to follow public firms. Panel A reports the evidence of EBR adoption leading to reduced capital market activities by public firms, where the dependent variables are (1) public firms' total financing activities (*Financing*), and (2) the number of shares traded for public firms (*Trading Volume*), respectively. Panel B continues to present the results for how reduced capital market activities lead to reduced analyst incentives. The dependent variables are (1) the number of analysts covering a public firm (#Analysts), and (2) the number of earnings forecasts issued for each public firm (#Forecasts), respectively. Columns 1 and 3 present the results for public firms experiencing greater reduction in financing activities (low & middle terciles) versus those experiencing lower reduction around business register adoption. *Drop1_Fin* and *Drop2_Fin* are middle and bottom tercile dummy variables based on the partitioning by change in financing activities (*ΔFinancing*) during the (-3, +3) period around business register adoption. Columns 2 and 4 present the results for public firms experiencing greater reduction in trading volume (low & middle terciles) versus those experiencing lower reduction around business register adoption. *Drop1_Vol* and *Drop2_Vol* are middle and bottom tercile dummy variables based on the partitioning by change in stock trading volume (*ΔTrading Volume*) during the (-3, +3) period around business register adoption. Lastly, Panel C shows how the reduced analyst incentives weaken the documented treated effect of business register adoption. The dependent variable is *Ferror*, calculated as the natural logarithm of the absolute value of the difference between the average analyst forecasted earnings and the actual earnings scaled by the absolute actual earnings. Column 1 presents the results for public firms experiencing lower analyst incentives (low & middle terciles) versus those experiencing higher analyst incentives around business register adoption. *Dec1_#Analysts* and *Dec2_#Analysts* are middle and bottom tercile dummy variables based on the partitioning by change in the number of analysts (*Δ#Analysts*) during the (-3, +3) period around business register adoption. The interaction terms *Post_BR*Dec1_#Analysts* and *Post_BR*Dec2_#Analysts* capture how the reduced analyst incentives (relative to higher analyst incentives) weaken the treated effect of business register adoption on improving analyst earnings forecast errors for public peer firms. Column 2 presents the results for public firms experiencing lower analyst incentives (low & middle terciles) versus those experiencing higher analyst incentives around business register adoption. *Dec1_#Forecasts* and *Dec2_#Forecasts* are middle and bottom tercile dummy variables based on the partitioning by change in the number of earnings forecasts issued (*Δ#Forecasts*) during the (-3, +3) period around business register adoption. The interaction terms *Post_BR*Dec1_#Forecasts* and *Post_BR*Dec2_#Forecasts* capture how the reduced analyst incentives (relative to higher analyst incentives) weaken the treated effect of business register adoption on improving analyst earnings forecast errors for public peer firms. Standard errors are clustered at country-year level, with t-statistics reported in parentheses beneath the coefficients. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All continuous variables are winsorized at the 1st and 99th percentiles. Please see Appendix A for detailed variable definitions.

Appendix A: Variable Definitions

Variable	Definition
Ferror	Measure for public firms' analyst earnings forecast errors, calculated as the natural logarithm of the public firm's absolute value of average analyst forecast errors in year *t*. The forecast error of each individual forecast is computed as the absolute difference between the actual earnings and the forecasts, scaled by the absolute actual earnings.
Post_BR	Indicator variable, taking the value of one for years after the electronic business register starts to operate in a firm's country and zero otherwise
Disclosure	Primary measure for private firm disclosure level, calculated as the natural logarithm of one plus the aggregate number of non-missing financial statement line items that private peers disclose in a given country and industry in year *t-1*, following Kim and Olbert (2022). The variable is standardized to have a mean of zero and a standard deviation of one.
ROA	Return on assets, defined as profit after tax in year *t* divided by total assets in year *t.*
MTB	Market-to-book ratio, calculated as market capitalization divided by book value of equity at the beginning of year *t.*
Size	Calculated as the natural logarithm of total assets in year *t.*
Loss	Indicator variable, taking the value of one if profit after tax is negative in year *t*, and zero otherwise.
Anano	Natural logarithm of total number of unique analysts covering the firm in year *t.*
Horizon	Natural logarithm of the average analyst forecast horizon, namely, the length of time between the forecasting date and the earnings announcement date in year *t.*
Sdeps	Natural logarithm of the time-series standard deviation of earnings per share over the ten years prior to year *t*.
FFIN	Indicator variable, taking the value of one if a firm has a higher than country-industry-year mean of scaled accruals in year *t*, and zero otherwise.
Stk_Exch	A score describing all the major stock exchanges on which a firm was listed in year *t*. A listing on any of the U.S. exchanges is given a weight of 1.5, a listing on all other exchanges is given a weight of 1. The scores for each firm are summed up in each year.
IFRS	Indicator variable, taking the value of one if the firm has adopted IFRS reporting in year *t*, and zero otherwise.
Financing	Total financing activities of public firms, calculated as (equity stock addition – equity stock reduction – purchase of treasury shares + long-term debt change) for year *t*, divided by total assets for year *t-1*.
Trading Volume	The natural logarithm of the number of shares traded for public firms in year *t*.
Drop1_Fin	A middle tertile indicator variable which equals to one if the *change* value of public firms' financing activities (*Financing*) is from the middle tertile group, and zero otherwise.
Drop2_Fin	A low tertile indicator variable which equals to one if the *change* value of public firms' financing activities (*Financing*) is from the bottom tertile group, and zero otherwise.
Drop1_Vol	A middle tertile indicator variable which equals to one if the *change* value of public firms' shares trading volume (*Trading Volume*) is from the middle tertile group, and zero otherwise.
Drop2_Vol	A low tertile indicator variable which equals to one if the *change* value of public firms' hares trading volume (*Trading Volume*) is from the bottom tertile group, and zero otherwise.
#Analysts	The number of analysts covering a public firm in year *t*.
#Forecasts	The number of earnings forecasts issued for a public firm in year *t*.
Dec1_#Analysts	A middle tertile indicator variable which equals to one if the *change* value of public firms' analyst coverage (*#Analysts*) is from the middle tertile group, and zero otherwise.

Dec2_#Analysts	A low tertile indicator variable which equals to one if the *change* value of public firms' analyst coverage (*#Analysts*) is from the bottom tertile group, and zero otherwise.
Dec1_#Forecasts	A middle tertile indicator variable which equals to one if the *change* value of public firms' earnings forecasts issued (*#Forecasts*) is from the middle tertile group, and zero otherwise.
Dec2_#Forecasts	A low tertile indicator variable which equals to one if the *change* value of public firms' earnings forecasts issued (*#Forecasts*) is from the bottom tertile group, and zero otherwise.
Disclosure_Pub	Measure for public firm disclosure level in year *t-1*, constructed analogously to *Disclosure.*
Pres_Priv	Private firm presence in an industry, calculated as the number of private firms divided by the number of private and public firms together in a country-industry in year *t-1*.
Size_Priv	Measure for the absolute size of private firms in an industry, calculated as the natural logarithm of the sum of total assets of all private firms for an industry in year *t-1*.
MedianSize_Priv	Natural logarithm of a country-industry-year's median private firm's total assets in year *t-1*.
MedianSize_Pub	Natural logarithm of a country-industry-year's median private firm's total assets in year *t-1*.
ROA_Priv	Aggregate return on assets (*ROA*) of private firms of a given country-industry-year defined as the sum of private firms' net income over the same firms' total assets in year *t-1*.
ROA_Pub	Aggregate return on assets (*ROA*) of public firms of a given country-industry-year defined as the sum of public firms' net income over the same firms' total assets in year *t-1*.
Revenue_All	Logarithm of the sum of revenues of all firms (public and private) of a given country-industry-year in year *t-1*.
Priv_Exposure	An indicator which equals to one if a public firm is exposed to at least one private firm (being its customers, suppliers, or competitors, respectively) in year *t*, and zero otherwise.
High_Timing_Overlap	An indicator which equals to one if a focal public firm's fiscal year has high overlap its private peer firms' information disclosure, and zero otherwise.
PE_Priv_Increase	An indicator which equals to one if an industry experienced an increase in total PE financing for private firms after the adoption of EBR, as compared with the period before the EBR adoption, and zero otherwise.

Appendix B: List of 39 Financial Statement Line Items in Orbis Database

Balance Sheet Items	Income Statement Items	Footnote Disclosure Items
Fixed Assets	Revenue	Number of Employees
Fixed Assets: Intangibles	Cost of Goods Sold	Export Revenue
Fixed Assets: Tangibles	Gross Profit	Labor Expenses
Fixed Assets: Other	Operating Expenses	Material Expenses
Current Assets	Earnings Before Interest & Taxes	Depreciation & Amortization
Current Assets: Stock	Financial Revenue	Interest Expense
Current Assets: Receivables	Financial Expenses	R&D Expense
Current Assets: Other	Earnings Before Taxes	
Cash	Tax Expense	
Total Assets	Net Income	
Equity Funds		
Equity Capital		
Equity Funds: Other		
Noncurrent Liabilities		
Noncurrent Liabilities: Long-term Debt		
Noncurrent Liabilities: Other		
Current Liabilities		
Current Liabilities: Loans		
Current Liabilities: Creditors		
Current Liabilities: Other		
Provisions		
Total Equity and Liabilities		

This table presents a list for 39 basic financial statement line items available in the Orbis database, including 22 balance sheet items, 10 profit and loss statement items and 7 footnote items (Kim and Olbert, 2022).

Appendix C: Sample Analyst Reports Discussing Private Firms

UBS's report on Dunelm Group dated 23 September 2024

We outline our methodology below.

Methodology:

Historical market size: To estimate the historic TAM for the UK Homewares and Furniture market, we use industry level data from ONS that aggregates furniture and furnishing annualized expenditure in the UK (in store + eCommerce) on a current price and seasonally adjusted basis.

Forecast: we used financials from private and publicly listed companies to both build a historical database and forecast our overall market estimate in future years. For the forecast years, we used UBS estimates (or consensus) for listed companies and our own forecasts for private companies to gauge industry performance in future years. We outline our key assumptions below:

- **Dunelm/B&M/NXT:** we use our model forecasts and in the case with B&M/NXT base our forecasts on estimated mix of Homewares in each business.

Dunelm Group 23 September 2024 UBS 11

Barclay's report on Carrefour's dated 20 September 2024

BARCLAYS

Equity Research
European Food Retail
24 September 2024

Carrefour

Deep dive on French market share reshuffle

We examine market share trends in France (where Carrefour's price investments are gaining traction) and the accounts of private peers. We expect Carrefour's top-line momentum in France to build, while FCF generation and French profitability look set to remain protected. Stock looks cheap on 7.4x 1Y FWD PE. Reiterate OW.

| CORE

CARR.PA/CA FP	OVERWEIGHT Unchanged
European Food Retail	NEUTRAL Unchanged
Price Target	EUR 19.00 Unchanged
Price (20-Sep-24)	EUR 15.55
Potential Upside/Downside	+22.2%

Appendix D: Disclosure Deadline for Private Firms in Treated Countries

Country	Disclosure Deadline	Legal Source
Austria	9-month	Unternehmensgesetzbuch (UGB)
Belgium	7-month	Code des sociétés et des associations (CSA)
Denmark	6-month	Danish Financial Statements Act (*Årsregnskabsloven*).
Finland	6-7 months after year-end	The Finnish Accounting Act (*Kirjanpitolaki*) & Limited Liability Companies Act (*Osakeyhtiölaki*)
France	7-month	Code de commerce, Art. L232-21, R232-21
Germany	12-month	Handelsgesetzbuch (HGB), §325
Greece	6-9 months after year-end	Law 4308/2014 (Greek Accounting Standards)
Hungary	5-month	Hungarian Accounting Act
Ireland	9-month	Companies Act 2014
Luxembourg	7-month	Law of 10 Aug 1915 on commercial companies & Law of 19 Dec 2002
Netherlands	8-month	Dutch Civil Code (*Burgerlijk Wetboek*), Book 2
Norway	7-month	The Accounting Act (*Regnskapsloven*) & The Register of Company Accounts (*Regnskapsregisteret*)
Poland	6.5-month (6-month + 15-day)	Accounting Act, Art. 52, 69
Portugal	6-8 months after year-end	Commercial Code (*Código Comercial*) & Accounting System of Companies (SNC)
Spain	6-7 months after year-end	Articles 253, 272, and 279 of the Ley de Sociedades de Capital
Sweden	7-month	Annual Accounts Act (*Årsredovisningslagen*)
United Kingdom	9-month	Companies Act 2006

This table presents a list for disclosing deadlines required by different EU countries in the treatment group. Column (1) shows the country name, column (2) shows the national-level disclosure deadline, and column (3) shows the reference to the legal source.