INFORMATION EXTERNALITY OF PAID-FOR-ANALYSTS

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CERTIFICATE OF ORIGINALITY

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________________________________ (Signed)

Jihye Yoo __ ________________ (Name of student)

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ABSTRACT

The implementation of the Markets in Financial Instruments Directive II (MiFID II) in 2018 has increased demand for paid analysts' research service in Europe. In this research, using a hand-collected dataset of the paid analysts' research service in Europe and employing a difference-in-differences research design, I find that financial analysts tend to make more accurate earnings forecasts for non-paying firms in the same industry of their paying firms than non-paying firms in the different industry after they are appointed as paid-for-analysts by the paying firms for their service. I also find that relative to non-paying firms with a better information environment, non-paying firms with weaker information environments tend to exhibit a greater level of improvement in analyst earnings forecast accuracy after the appointment of the analysts for their research services. Similarly, I also find that paid-for-analysts tend to cover more non-paying firms in the same industry of their paying firms after their appointment of paid-for-analysts. Overall, the findings of this study are consistent with the conjecture that paid-for-analysts' greater level of access to paying firms' private information facilitates their earnings forecasts of non-paying firms.

Keywords: Paid-for-analysts, MiFID II, Information Externality

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1. **Introduction**

Paid-for-analysts are the equity research analysts who get paid by corporate issuers in return for providing their research coverage services. As a series of regulatory changes in the securities industry have resulted in the shrinkage of sell-side analysts' coverage of small to mid-cap stocks globally, the demand from companies for paid analysts' research service has risen (Billings et al. 2014). Most recently, the implementation of the Markets in Financial Instruments Directive II (MiFID II, a regulation that requires asset managers with European clients to unbundle their research cost from execution trading costs) in 2018 has further increased demand for paid analysts' research service. Accordingly, more than 900 companies in Europe paid for equity research coverage in 2019, and the number is increasing. However, most of the research analysts studied in academic research are sell-side analysts, who get paid by investors through trading commissions. Due to the atypical incentive scheme between the companies and paid-for-analysts, studies on paid-for-analysts can allow us to understand from a fresh lens the mechanisms of how analysts integrate information to forecast earnings. Furthermore, MiFID II implementation triggered some of the traditional sell-side research houses to start a paid-for-research business to complement their declining revenue in Europe. This is the first study that identifies an emerging practice of equity research analysts who both cover research-paying companies and non-paying companies[1] in traditional sell-side research houses and examine the existence of information externality of these analysts.

A few studies about paid-for-research include the characteristics of the paying companies that hire analysts for the research coverage and the quality of such research relative to the traditional sell-side research. Companies that hire a fee-based research firm are usually not covered or thinly covered by mainstream sell-side analysts due to their small market

[1] In this study, 'paying companies' are defined as the companies that appoint equity research analysts and pay the research coverage service fee. 'Non-paying companies' are defined as the companies that the sell-side analysts choose to cover. These companies don't pay the research service fee to the analysts.

capitalization, low trading liquidity, or high business uncertainty (Kirk 2011). As the paid-for-analysts' incentive scheme is different from that of sell-side analysts, many capital market participants are concerned about the potential conflict of interest between paid-for-analysts and investors. Even mass media, such as Wall Street Journal, warned of the rise of sponsored stock research and compared it to the credit rating research[2], which brought in ominous results in the 2008 debt crisis.[3] Nevertheless, prior literature concludes that paid-for-research provides information content to investors comparable to that of sell-side analyst reports (Billings et al. 2014). Both studies claim that the paid research carries the value relevant information to investors in the short term (Kirk 2011) and long term (Billings et al. 2014) investment horizon. In this research, I discover an emerging practice of sell-side analysts who both analyze research-paying companies and non-paying companies (here and after I name them as 'paid-for-analysts' in this paper) in the European sell-side research houses and explore the information spill-over effect from paying companies to non-paying companies.

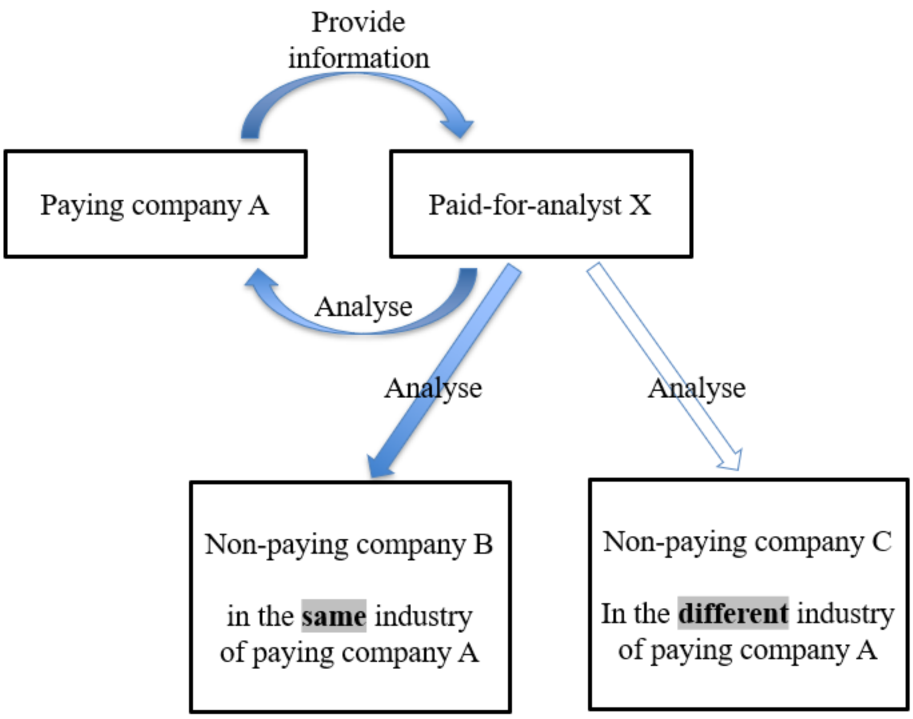
Paying companies pay analysts for research coverage because such companies are not voluntarily covered by sell-side analysts due to the size, liquidity, or a lack of institutional investors' interests. When paying companies pay for the coverage service, they have high incentives to provide information to equity analysts. For example, companies hire investor relations (IR) programs and provide information to IR firms to attract investors, financial analysts, or media (Bushee et al. 2012). At the same time, analysts' knowledge of the industry or their access to corporate information is a major substance for accurate earnings forecasts. Other than the company's public disclosures, analysts collect information through private calls with management, site visits, channels-checks through competitive companies, etc. Due to paying companies' high incentives to provide information and analysts' effective usage of the

[2] Unlike equity research, bond rating research are paid by issuing companies.
[3] 'The Dangerous Rise of Sponsored Stock Research', 2018, WSJ, https://www.wsj.com/articles/the-dangerous-rise-of-sponsored-stock-research-1543400111

acquired information, I conjecture that the forecast earnings accuracy will improve for the non-paying companies in the same industry of paying companies compared with those in the different industry of paying companies after the analyst gets information from paying companies. I apply difference-in-difference research design to examine the earnings forecast properties of paid-for-analysts using the hand-collected dataset of the paid-for-research analysts who cover both paid- and unpaid-for-research in Europe.

To illustrate, consider a setting with firms A, B, and C covered by analyst X. Firm A is a ‘paying company’ while firm B and firm C are ‘non-paying companies’. In this study, ‘paying companies’ are defined as the companies that appoint equity research analysts and pay the research coverage service fee. ‘Non-paying companies’ are defined as the companies that the sell-side analysts choose to cover. These companies don’t pay the research service fee to the analysts. Firm A and firm B are in the same industry, whereas firm C is in a different industry from firm A. Analyst X starts to cover firm A and get service charges from firm A on a certain date. Figures1 illustrates this.

Figure 1. A Setting of the research; paid-for-analyst, paying-company, and non-paying companies



I hypothesize that covering company A helps analyst X improve the accuracy in forecasting the earnings of non-paying company B to a greater degree than that of non-paying company C. Analysts are expected to improve their forecast accuracy for firm B more than firm C for the following reason. The industry knowledge of analyst X improves after covering company A by getting provided with more industry-relevant information from company A. Paying companies choose to pay the analysts for the research coverage because they are less covered by sell-side analysts (Kirk 2011). As they actively approach research analysts to be covered, paying companies have strong incentives to provide in-depth industry knowledge or business background to paid-for-analysts. Therefore, paid-for-analysts are expected to develop the specific industry knowledge more after they cover paying companies.

All previous paid-for-analysts research are about those analysts who work for paid-for-research-house only, i.e., pure research firms that don't have brokerage business. Therefore, most of these analysts cover paying companies only, which are smaller, less liquid, less covered by companies that are not covered by sell-side analysts. Billings et al. (2014) is the first research to investigate the value of the paid-for-analysts comparing with sell-side analysts. They document that the paid-for-research provides value to long-term investors comparable to that of matched sell-side analysts. However, there is no study about research analysts who both cover paying companies and non-paying companies at the same time. The group of these research analysts has emerged as a result of MiFID II implementation. This study fills the void by providing the analysis of an emerging practice of such paid-for-analysts.

I find that among firms covered by the analysts, analysts tend to make more accurate earnings forecasts for firms in the same industry of their paying firms than firms in the different industries after they are appointed as paid-for-analysts by the paying firms for their service. In other words, the finding suggests that relative to the period when analysts did not get paid for their earnings forecast, analysts' earnings forecast accuracy of firms in the same industry of their paying firms improves after they become the paid-for-analysts. I also find that paid-for-analysts tend to cover more firms in the same industry of their paying firms after they are appointed as paid-for-analysts by the paying firms. Overall, the findings of this study are consistent with the conjecture that paid-for-analysts' greater level of access to paying firms' private information facilities their earnings forecasts of non-paying firms.

In the following section, I review the relevant literature. Section 3 provides background regarding the rise of the paid-for-analysts following the MiFID II in Europe, and the main hypotheses. Section 4 outlines the data and descriptive statistics followed by research design and results in section 5. Section 6 concludes the study and shares further research ideas.

2. **Literature Review and Contributions**

This research contributes to the three areas of literature. First, it adds to the literature of information spill-over channels for research analysts, especially in the form of information externality. Prior literature has documented the analysts' spill-over channels in several aspects.

Pandit et al. (2011) find information externalities of analysts along the supply chain. Hilary and Shen (2013) examine the intra-industry information transfer effect of research analysts. When a firm announces its management forecast, the longer the analysts have covered the company, the higher forecast accuracy they make for other companies in the same industry. Hwang et al. (2019) find the information sharing and spill-overs of financial analysts in the same broker by investigating their forecast accuracy of the merged firms prior to the M&As. Li et al. (2020) find the information spill-over from privately connected analysts to non-connected analysts by analyzing the forecast accuracy of non-connected analysts following the termination of coverage by the connected analysts. Luo et al. (2015) provide evidence of how analysts use the information externality effect to construct their portfolios by investigating supply chain analysts. This study suggests another information spill-over channel, especially the information externality by paid-for-analysts, through exploring the event of getting paid by paying companies for their research services.

Second, it relates to the paid-for-research literature. Despite the increase in demand for paid-for-analysts, academic research about the externalities of paid-for-analysts is limited. A few exceptions include Kirk (2011) and Billings et al. (2014). They examine the properties of the paid-for-analysts (Billings et al. 2014) and research-paying companies (Kirk 2011) but are limited to the analysts who solely cover paying companies in the US. This research broadens the paid-for-analysts research in two aspects. Firstly, the sample covers the paid-for-analysts in Europe. Europe has noticed a substantial increase in the paid-for-research industry, particularly after implementing MiFID II regulation. Secondly, this research specifically identified and analyzed the paid-for-analysts who work for sell-side research houses. This identification is critical to discover the information externality of research analysts. Normally, sell-side research houses and paid-for-research houses are exclusive and have different incentives. Prior research was only able to focus on the paid-for-analysts hired by the paid-for-research specific house. However, as being influenced by MiFID II implementation, some of the traditional sell-side research houses started to cover paid-for-research in addition to the existing sell-side research service. By focusing on this specific identification, we could partly understand the information externality of paid-for-analysts.

Lastly, it is one of the few research papers that analyses the effects of MiFID II on the capital markets. MiFID II is considered to be the most impactful regulatory change in the management industry. The affected party includes asset managers, investment banks, brokers, traders, and companies within the EU. For example, not only the European asset managers but also the non-European asset managers trading European listed stocks or trading with European investment banks also should abide by this regulation. Fang et al. (2020) document the broad changes in sell-side analysts and buy-side analysts affected by the new regulation. They find a decrease in the number of sell-side analysts covering European firms after MiFID II implementation, particularly for less important firms to the sell-side. Their finding is in line with the anecdotal evidence of the increase in demand for the paid-for-research. By identifying the emergence of paid-for-analysts in sell-side research houses and examining their improvement of forecasting earnings for non-paying companies, this research explains one of the unexpected effect of MiFID II on capital markets.

3. Background and Hypotheses

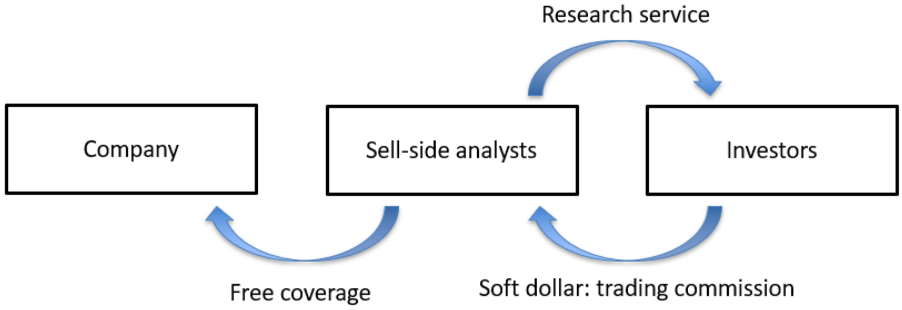
3.1. What is paid-for-analyst?

Most of the financial analysts are sell-side analysts who work for investment banks. Their incentives to cover the companies or the analysis properties are highly influenced by the relationship with their employers (investment banks), investors, and companies. Sell-side analysts typically initiate company reports based on investor's interest and cost of covering a firm (Barth et al. 2001) because their revenue comes from investors' trading commissions. On the other hand, sell-side analysts tend to be over-optimistic due to strategic business concerns, especially when their employers have underwriting relationship with a company (Dugar and Nathan 1995; Lin and McNichols 1997), or they are concerned about losing access to the company management if negative reports are published (Francis and Philbrick 1993).

Paid-for-analysts, however, have different incentives from sell-side analysts. The paid-for-analysts don't get trading commissions from investors. Usually, most paid-for-analysts are hired by paid-for-research houses, which don't have agency or brokerage businesses. Therefore, paid-for-analysts are less concerned about losing information access if they publish unfavorable reports on the covering companies or declining trading commissions by getting less attention from investors. On the contrary, people raise a concern about the conflict of interest between investors and companies, as paid-for-analysts provide research based on the service fee from companies. Most companies pay analysts with the purpose of gaining investor exposure.

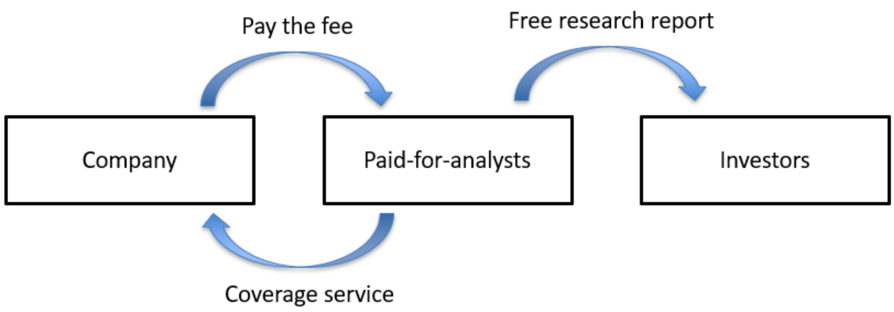
Figures 2A and 2B illustrate the difference between sell-side analysts and paid-for-analysts. Sell-side analysts provide research service to investors and get a trading commission as bundling costs. It is analysts' will (though highly influenced by brokerage firm management) to decide which company to cover. As they get commissions from investors, they have more incentive to maintain coverage of the companies, which are (or expected to be) favored by institutional investors, have high earnings visibility, or are generally large caps.

Figure 2A The relationship between sell-side analysts, companies, and investors



On the contrary, paid-for-analysts are chosen by companies and provide coverage service to paying companies. The coverage service varies depending on the contract but mostly includes regular research reports and investor access. These research reports are usually open to the public for free. In this case, companies are willing to provide business information more actively than non-paying companies by helping analysts collect industry-relevant information more easily.

Figure 2B. The relationship between paid-for-analysts, companies, and investors



A series of regulatory changes in the securities industry have resulted in the shrinkage of sell-side analysts' coverage of small to mid-cap stocks globally. Accordingly, the demand for the paid-for-analysts has risen over the period despite the concern on potential conflict of interests. Companies that hire a fee-based research firm to prepare research reports are usually not covered or thinly covered by sell-side analysts due to their small market capitalization, low trading liquidity, or high business uncertainty (Kirk 2011). Paid-for research reports do not present the recommendation of the stock on the research report but only present forecasts.[4] In the paid-for research report, it is usually disclosed that once the research contract is made between research houses and paying companies, paid-for-analysts keep their objectiveness to analyze the company.

[4] There are some paid-for-research which provide stock recommendation. (Prior research, 2014) analysed the recommendation quality of paid-for-research. But none of paid-for-research in our sample provided the stock rating or recommendation.

3.2. MiFID II and the rise in paid-for-analysts in Europe

Markets in Financial Instruments Directive II (MiFID II) is a regulation that requires asset managers with European clients to unbundle their research costs from execution trading costs implemented in 2018. All companies listed in the European stock market (including London), European asset managers, and European brokerage and investment banks should follow this regulation. Non-European asset managers or non-European banks also should abide by this rule if they trade with European clients. The purpose of this rule is to offer greater protections for investors and provide more transparency to financial markets. Before this regulation, asset managers pay soft-dollar to investment banks or brokers upon receipt of analyst research reports, brokerage client service, and other miscellaneous costs through bundled trading costs. These trading commissions become part of the fund costs that investors have to bear. The new regulation prohibits the bundled fee system. Asset managers should separate trading execution fees paid to brokers from the cost of conducting research. Asset managers should be incentivized to find brokers that provide the best execution at a minimum trading fee while using their own revenue from management fees to pay for research analysts' services.

A few research studies on the impact of MiFID II find that the new regulation achieves the objective of investor protection. The quality of analysts' forecasts has improved after MiFID II implementation, and buy-side analysts try to be more active in carrying out their stock analysis. At the same time, MiFID II brought out the decrease in analyst stock coverage (Lang et al. 2019; Fang et al. 2020) and this leads to a further increase in the demand for paid-for-research. Various anecdotal sources say the substantial growth of paid-for-research in European markets since MiFID II implementation. Nasdaq revealed a 50% increase in paid-for-research by September 2019 since MiFID II was introduced (Bloomberg, Nasdaq, 2019) from around 300 companies to 450 companies in the Nordic stock market. French company-sponsored research also increased from 289 in December 2017 to 368 in June 2019 (AMF, 2019).

The increasing demand for paid-for-research is due to the change of relative cost of the analyst research after MiFID II. Asset managers have to pay the fee to brokers in order to get the sell-side analysts' service, which was previously included in the trading commission. Prior to new regulation implementation, the formal fee for research reports was free for both sell-side and paid-for-research. After the regulation, sell-side research needs payment directly from investors while paid-for-research remains free to investors, making the relative cost of sell-side research higher while that of paid-for-research is lower.

Accordingly, the new regulation leads some existing sell-side research houses or investment banks to expand their business to paid-for-research. Asset managers are no longer allowed to pay soft commissions for investment research with their clients' money, i.e., asset under management (AUM). Instead, asset managers have to pay for the sell-side research as part of their operating expenses. As a result, asset managers' ability and willingness to pay commissions to investment banks for sell-side research declined substantially, which in turn led investment banks to reduce the overall number of research analysts they employ. On the contrary, since paid-for-research is free to read by any asset managers, issuers (often those whose coverage is dropped off by the traditional investment banking research department) become more willing to pay for such service to have their business model analyzed and their earnings forecasts become available for asset managers. More interestingly, some of the traditional investment banks in Europe (e.g., Nordea) have started publishing commissioned-sponsored research as part of their restructured, hybrid business model. This change allows us to obtain a unique dataset of analysts who produce both paid-for-research and traditional sell-side research.

3.3 Hypotheses

Analyst coverage is one of the essential factors for public companies to increase firm visibility in the capital markets. Analyst coverage not only helps companies attract more institutional investors and other analysts' coverage (Kirk 2011), it also makes the market respond with increased liquidity (Irvine 2003; Crawford et al. 2012). Therefore, some companies neglected by sell-side analysts look for paid-for-analysts to get exposed to more investors. As these companies are willing to pay for the research coverage service and they are not followed by many analysts, they actively provide information to analysts (Hamrouni et al. 2017; Anantharaman et al. 2011). At the same time, analysts' knowledge of the industry or their access to corporate information is a major ingredient for accurate earnings forecasts. Other than companies' public disclosures (Lang et al. 1996; Dhaliwal et al. 2012), analysts collect information through private calls with management (Bradshaw 2011; Green et al. 2014; Chen et al. 2006; Green 2006; Mayew 2008; Soltes 2014), site visits (Cheng et al. 2016), channels-checks through competitive companies (Pandit et al. 2011; Luo et al. 2015), etc. Some analysts allocate the portfolio to maximize utilization of the industry knowledge (Luo et al. 2015). Especially for the first coverage of the company, analysts tend to produce more industry- and market-wide information (Crawford et al. 2012).

Prior studies have shown that firms have strong incentives to provide information when such activity increases firm visibility to gain investor attention and lowers the cost of capital. Voluntary disclosure improves analyst coverage and investors' interest (Lang and Lundholm 1996; Graham et al. 2005) and reduces firms' cost of capital (Sengupta 1998; Dhaliwal et al. 2011). For example, small firms hire IR programs and provide information to improve institutional ownership, media coverage, and analyst following (Bushee and Miller 2012). Paying companies are small, illiquid, and less visible. They expect more visibility in capital markets by connecting with financial analysts and actively give the information. At the same time, access to management is critical for analysts to collect relevant information. Such acquired information would influence analysts when they analyze other companies, especially when the companies are in the same industry of paying companies. However, as paying company has different features from non-paying companies, someone can argue that the information obtained from paying companies would not be relevant to analyze the non-paying companies even though they are from the same industries. I hypothesize that due to paid-for-analysts' better access to paying firms' private information resulted by firms' stronger incentive to disclose business-related information in facilitating better analysts' forecasts can have the potential to help analysts to make better earnings forecasts for firms in the same industry of the paying firms than those in the different industries. The first hypothesis is, thus, as follows.

H1: Relative to non-paying firms not in the same industry of paying firms, the earnings forecast accuracy of non-paying firms in the same industry of the paying firms covered by the analysts improves after the analysts are appointed as paid-for-analysts by the paying firms.

Next, I hypothesize that the information externality effect of getting appointed as paid-for-analysts by the paying firms would be stronger with the weaker information environment of non-paying companies. Private information the paid-for-analysts get from paying companies will be more beneficial when analyzing the non-paying companies in the same industry of the paying companies, especially when non-paying companies are with weaker information environments.

H2: Relative to non-paying firms with better information environment, non-paying firms with weaker information environment exhibit a greater level of improvement in earnings forecast accuracy after the analysts are appointed as paid-for-analysts by the paying firms.

Next, I examine how analysts change their coverage after getting paid by paying companies. The process of forecasting company earnings is costly (Clement 1999; Hong et al. 2000), and analysts strategically allocate their resources to choose the coverages to construct the portfolio (Luo et al. 2015). Barth et al. (2002) find that analysts' coverage decreases in the effort that analysts expend to follow the firms. After getting more value-relevant information from paying companies, analysts have incentives to follow similar firms. On the contrary, as the process of forecasting company earnings is labor-intensive, analysts may choose to substitute the non-paying companies with paying companies if both are from the same industry. They would prefer focusing their labor on the paying companies that easier management access facilitates the analysis process and dropping the coverage of similar companies. I hypothesize that analysts will increase the coverage of the firms in the same industry of the paying companies relative to the companies in the different industries after they initiate the coverage for paying companies.

> **H3: After the analysts are appointed as paid-for-analysts by the paying firms, they tend to cover more non-paying firms in the same industry of their paying firms than non-paying firms in different industries of the paying firms.**

4. Data and descriptive statistics

In this section, I explain the sample data[5] and present the descriptive statistics to show the characteristics of paid-for-analysts and the differences between paying companies and non-paying companies.

To examine the information externality of paid-for-analysts, I identify a sample of paid-for-analysts in sell-side brokers by hand-collecting the list of paying companies. I find three European sell-side research houses[6] (two of them are investment banks and one is an

[5] Detailed sample construction is descripted in Appendix A.
[6] Nordea, AlphaValule, Exane BNP Paribas. Mostly paid-for-research is covered by paid-for-research house, who only cover paying companies without any brokerage business.

independent research house) that cover paying companies, by web-search such as ‘Issuer-paying research’, ‘commissioned research’, ‘paid for research’, or ‘company-sponsored research’[7]. All the paid-for-research reports of these three brokers are available online for free[8], while their traditional sell-side research reports are not open to the public for free. I generated a list of paying companies of those brokers and matched it with analyst code from the Institutional Brokers’ Estimate System (I/B/E/S) database to find brokerage code and collect each analyst’s coverage of those research houses.

I obtain the data on analysts’ EPS forecasts from I/B/E/S database over the period January 2017- October 2020. I cross-checked whether the date of paying company in I/B/E/S is consistent with the actual report published on each broker’s website. Company financial data and stock price data are from Compustat Global, and management guidance data is collected from Capital IQ. Table 1 reports the procedures on how I constructed the sample for the main analysis. All estimates are next fiscal year’s earnings per share. As the focus of this study is to examine the information externality for the non-paying firms, I remove analysts’ earning estimates for paying companies from the sample. This study imports difference-in-difference research design, using the coverage initiation date for each paying company as an event date. I remove the estimates made one year before or after the event of each paying company’s coverage initiation for the difference-in-difference analysis. Lastly, the outliers identified by studentized residuals are removed for the regression to get the final sample of 3,482 estimates.

[Insert Table 1 about Here]

Table 2 describes the descriptive statistics (Panel B) of paid-for-analysts. We have a total of 32 paid-for-analysts[9] from three brokers who cover both paying companies and non-

[7] I followed the method of Marcus Kirk (2011) and Billing et al. (2014) to identify the paid-for-analysts.
[8] The research open to public is available for a certain period. Usually between 2-4 years.
[9] For the empirical analysis, I delete two analysts, which are outliers, who get appointed as a paid-for-analyst by more than ten paying companies from the sample. Excluding these two analysts, each paid-for-analyst covers an average of 1.7 paying companies.

paying companies. Thirty analysts are appointed as a paid-for-analyst by less than five paying firms, and 18 such analysts provide the research coverage service to one paying company. On average, each paid-for-analyst covers 2.39 paying companies during the sample period. The median is 1.81. Panel B shows the descriptive statistics of paid-for-analysts in the firm-year-analyst observations. The mean value of the firm market cap is US$ 7.0 billion and the median value is US$ 2.5 billion. The sample paid-for-analysts follow 18 companies on average during the period. About 10% of their coverages are paying companies[10]. Each firm is followed by eleven analysts in the sample. On average, the sample paid-for-analysts update the earning forecasts five times per year for each company. Their experience as a financial analyst is 12 years and they have been following each company for 4.5 years.

[Insert Table 2 about Here]

The next table shows characteristics of the paying companies and non-paying companies in the sample. In Table 3, Panel A shows firm-year descriptive statistics for paying companies and non-paying companies covered by paid-for-analysts during the sample period. About 10% of the total universe is the paying companies. Consistent with prior literature (Kirk; 2011, Billing et al.; 2014), paying companies have a smaller market cap, less analyst following, and lower analyst forecast frequency than non-paying companies. Paying companies' average market cap is US$ 299 million while non-paying companies' average market cap is US$ 7,186 million. Paying companies are followed by 3.6 analysts while non-paying companies are covered by 11.5 analysts on average.[11] In our sample, a book to market ratio of paying companies is higher than that of non-paying companies.

Panel B presents the distribution of full sample observations by industry for both non-paying and paying companies. It follows the Barth et al. (1998) 23 industry classification. I

[10] The average number of paying company coverages per analyst divided by the total number of coverage per each analyst. 1.7/18=9.4%

[11] Usually paying companies are covered by paid-for-analysts only.

note that Insurance/Real Estate represent 18.3% (17.4%) of the full (non-paying companies) sample, followed by Textiles/Print/Publish 9.0% (8.3%) and Mining/Construction 8.8% (9.4%).

[Insert Table 3 about Here]

5. Research Design and Results

First, I assess the informativeness of paid-for-analysts' earning forecasts for non-paying companies by testing whether the analysts' forecast properties change after getting appointed by paying companies paid for their research service. I apply the following difference-in-difference regression model to assess whether the analysts' forecast accuracy improves for the non-paying companies in the same industry of the paying companies relative to those in the different industries after a paying company appoints the analyst to provide the research service. I determine the event date when an analyst publishes the first research report for a particular paying company.[12]

$$Accuracy_{i,j,t} = \alpha + \beta\, POST \times TREAT + POST + TREAT + Controls \quad (1)$$

I measure forecast accuracy using the absolute value of forecast error, the actual earnings per share minus forecasted earnings per share, scaled by price, $Accuracy = \frac{|Actual\ EPS - Forecast|}{Price}$. The exchange rate to scale the data is used as of the actual earning announcement date. The lower the *Accuracy* is, the more accurate the analyst forecast earning is. *POST* indicates one if the paid-for-analyst' earning estimate for a non-paying company is announced after the analyst starts to cover a paying company and 0 otherwise. *TREAT* indicates one if the non-paying company is in the same industry of the paying company and 0

[12] If a paid-for-analyst covers *n* paying companies, the analyst has *n* different event dates.

otherwise.[13] I expect the coefficient β would be negative, indicating that paying companies provide relevant information to paid-for-analysts and that information help the analysts to improve their forecast accuracy for non-paying companies in the same industry of the paying companies compared to those in the different industries. Control variables include firm control variables and analyst control variables that are widely included as determinants of analyst forecast accuracy. A detailed definition of all variables is presented in Appendix C.

Table 4 presents the primary result of the difference-in-difference regression model. As we predicted, column (1) exhibits a negative coefficient for *POST*TREAT* variable at the 5% significance level. Forecast accuracy for non-paying companies in the same industry of the paying companies improves more than those in the different industries after analysts are appointed by paying companies as paid-for-analysts for their research services. It supports the information externality of paid-for-analysts by covering the paying companies. Column (2) shows that the event of getting paid by paying companies does not affect the forecast accuracy of the paid-for-analysts. Column (3) presents that there is no difference in forecast accuracy of the non-paying companies for the paid-for-analysts whether the non-paying companies are in the same industry of the paying companies or not.

[Insert Table 4 about Here]

To test hypothesis 2, I use firm size and management voluntary disclosure of non-paying companies to proxy for information environment. Most paying companies are mid to small-cap companies (Kirk 2011; WSJ 2018; Bloomberg 2019), market cap below US$1bn. The benefit of acquiring information from paying companies would be higher for analyzing the small size companies in the same industry of the paying companies than the large size

[13] For industry classification, I use 4 different classification including 2-digit SIC, 4-digit GICS, Fama-French 48 industries, and Barth et al. (1998) 23 industries. All presented results in tables use Fama-French 48 industries. Results are robust for other industry classification except for the SIC classification. It could be due to the high number of SIC classification, which would be less proper for this relatively small sample.

companies because the relative value of such information will be more critical for small companies than large companies. Similarly, I use firms' voluntary disclosure as another proxy for the information environment of firms. Companies' voluntary disclosures provide a better information environment for market participants (Muslu et al. 2015; Cormier et al. 2014). The value of private industry information obtained from paying companies for analysts would be more effective when analyzing the non-paying companies without the managements' voluntary disclosures than those with the disclosures.

To test the first proxy, I divide the total sample into two groups by market cap size of non-paying companies. The company is categorized as a small (large) cap if the market cap is below (above) the median of the total firm-year observation, which is $2.5bn.

I apply regression model (1) to each size group, respectively, expecting the coefficient β to be negative, especially for the small-size company group. Panel A of Table 5 presents the result of the difference-in-difference regression model of both size groups. Coefficients of *POST*TREAT* in Column (3) and column (6) are our focus. As expected, forecast accuracy for the small companies in the same industry of the paying companies has improved after the analysts get paid by paying companies for their research services. The coefficient of *POST*TREAT* variable is negative with a t-value of -2.2 and a p-value of less than 2%. The positive externality of information is observed in small size companies. The absolute value of the coefficient also increases from 0.003 of the total group to 0.005 of the small-cap group. Information provided by paying companies helps paid-for-analysts improve their forecast accuracy for other companies in the same industry of the paying companies, especially for small non-paying companies.

On the contrary, the coefficient of *POST*TREAT* is negative but not significant for the large size group. Analysts do not benefit from getting information of paying companies for the analysis of other large-cap companies. Interestingly, the coefficients of the variable *POST* in column (4) and (6) are significantly positive, indicating that covering paying companies have a negative effect on the forecast accuracy of large-cap size companies (4), especially when they are in the different industries of paying companies (6).

In addition, I use a difference-in-difference regression model below to support the hypothesis;

$$Accuracy_{i,j,t} = \alpha + \beta\, TREAT_{SMALL} \times POST + \gamma\, TREAT_{LARGE} \times POST + POST + TREAT_{SMALL} + TREAT_{LARGE} + Controls \quad (2)$$

where $TREAT_{SMALL} = TREAT \times SMALL,$ and SMALL is defined as

$$SMALL = \begin{cases} 1 & is\ market\ cap\ of\ company\ j < median\ market\ cap \\ 0 & otherwise\ . \end{cases}$$

Similarly, the dummy variable $TREAT_{LARGE}$ is defined as

$TREAT_{LARGE} = TREAT \times LARGE,$ where LARGE is defined as

$$LARGE = \begin{cases} 1 & is\ market\ cap\ of\ company\ j \geq median\ market\ cap \\ 0 & otherwise\ . \end{cases}$$

The untabulated result is in line with Panel A of Table 5. Analyst forecast accuracy for small size non-paying companies in the same industry of the paying companies improves after analysts get provided the service fee from the paying companies. Overall, the results show an improvement in analysts' forecast accuracy for the non-paying companies, especially when they are small-size and in the same industry of the paying companies relative to the large-size companies. The presence of paid-for-analysts creates a positive information externality for the information environment of the non-paying firms.

Similarly, to test the second proxy, I divide the total sample into two groups by whether the companies voluntarily disclose management revenue guidance. Management guidance is critical information for analysts (Chapman et al.: 2018) to analyze companies and industry. I apply regression model (1) to each group, respectively, expecting the coefficient β to be negative, especially for the group of companies that did not provide management guidance. Panel B of Table 5 presents the regression result of the difference-in-difference model for both groups. As expected, the coefficients of *POST*TREAT* in Column (3) and column (6) show the difference between the two groups. In column (3), the coefficient of *POST*TREAT* is -0.004 with the t-stat value of -2.519 for the group of non-paying companies that didn't disclose management guidance. The absolute value of the coefficient (-0.004) and t-value (-2.519) are marginally larger than those of the total sample, which are -0.003 and -2.055, respectively. The non-paying companies in the same industry of the paying companies exhibit a significant improvement of forecast earnings after the appointment of the analysts for their research services, especially when the non-paying companies did not announce the revenue guidance.

On the contrary, when the non-paying companies voluntarily disclose the management forecast, the information externality effect is not revealed. The coefficient of *POST*TREAT* in column (6) is not significant. Analysts do not experience the improvement of forecast earnings for the non-paying companies that voluntarily provide management forecasts, even though such companies are in the same industry of the paying companies that those analysts cover. Overall, the results support the conjecture that the information externality of paid-for-analysts is more effective with weaker information environments.

[Insert Table 5 about Here]

Next, I perform the regression to test hypothesis 3. $Ind\_Cvg_{i,j,t,}$ (*Industry Coverage*) is the number of companies, which analyst *i* covers, in the same industry of a company *j* at time *t*. We test whether analysts increase the coverage for the non-paying companies in the same industry of their paying firms more than non-paying companies in the different industries, after the analysts are appointed as paid-for-analysts by the paying firms. I use the following difference-in-difference regression model, and other variables are as same as those in the regression model (1). As it takes time for analysts to decide the new coverage, I remove the analyst earning forecasts announced before or after 180 days of the first coverage of paying companies from the initial sample. I expect the coefficient β to be positive, indicating that analysts increase the coverage for the firms in the same industry of the paying companies, after they initiate the coverage for the paying companies.

$$Ind\_Cvg_{i,j,t} = \alpha + \beta\, POST \times TREAT + POST + TREAT + Controls \quad (3)$$

Similarly, I add another dependent variable, *Ind_wgt*, to measure the ratio of the companies in the same industry of a covering company (Ind_Cvg) to the total number of coverages of the analyst (*Coverage*):

$$Ind\_Wgt_{i,j,t} = \frac{Ind\_Cvg_{i,j,t}}{Coverage_{i,t}}$$

If $Ind\_Wgt_{i,j,t}$ is 1, all coverages of the analyst *i* are in the same industry of company *j* at time *t*. If $Ind\_wgt_{i,j,t}$ is .5, half of the companies among analyst *i*'s coverages are in the same industry of company *j* at time *t*. The correlation between *Ind_Cvg* and *Ind_Wgt* is around 0.6.[14] While *Ind_Cvg* counts the absolute number of companies that analysts cover in a certain industry, *Ind_Wgt* presents the relative industry weight of the analyst's portfolio. *Ind_Wgt* complements *Ind_Cvg* when we focus on the change of the variables. For example, consider that auto industry coverage (*Ind_Cvg*) increases from 4 to 5, and the total coverage of the analyst increases from 10 to 13. The auto industry weight for the analyst (*Ind_Wgt*) declines from 40% to 38% even though the absolute number of auto industry coverage (*Ind_Cvg*) increases. To better support hypothesis 3, I use two dependent variables of the analyst's absolute and relative industry coverage.

[14] For four different industry classifications, the correlations between Ind_Cvg and Ind_Wgt are 0.59 (Fama-French), 0.66 (GICS 2-digit), 0.65 (Berth), and 0.59(SIC 2-digit), respectively.

Table 6 presents the regression results of covering paying companies on the coverage of non-paying companies. Two dependent variables exhibit similar results. As expected, analysts significantly increase the coverage for the same industry of the paying companies after initiating the coverage for the paying companies. Columns (1) to (3) are the results of the regression (3), where the dependent variable is *Ind_Cvg*. Columns (4) to (6) are where the dependent variable is *Ind_Wgt*. The coefficients of *POST*TREAT* in column (1) and column (4) are positive at the 1% significance level. The coefficients of *POST* in column (1) and column (4) are significantly negative, which indicates that analysts' coverages for the non-paying companies in the different industries decline after getting paid by paying companies. The significant positive coefficient 0.659 of the variable *TREAT* in column (3) and 0.040 of the variable *TREAT* in column (6) indicates that the analyst coverage for the companies in the same industry of the paying companies is higher than those in the different industry. This result shows that paying companies choose analysts who are experts in the company's industry. Overall, the result supports the hypothesis that industry allocation of analysts' coverage is affected by providing the service to paying companies.

[Insert Table 6 about Here]

6. Conclusion

By identifying the new group of analysts, the paid-for-analysts who cover both paying companies and non-paying companies in the sell-side brokers, this research finds the positive information externality of paid-for-analysts using the dataset of European companies. Industry participants are concerned about the rise of the paid-for-research after the MiFID II implementation, arguing that paid-for-research will provide paying-company-favoured research at the expense of investors. However, I find that getting a direct fee from the paying firms for analysts has a positive effect on analyzing the earnings of non-paying firms as these analysts have better access to paying firms' private information.

This research contributes to the literature in several aspects. First, it suggests a new information spill-over channel for research analysts, especially in the form of information externality. Second, it extends the scope of the paid-for-research literature. Only a few papers have examined the properties of the paid-for-analysts and research-paying companies but are limited to the analysts who solely cover paying companies in the US. Lastly, it contributes to the research on the effects of MiFID II on the capital markets. It also supports the practitioners in capital markets, documenting the positive impact of the paid-for-research for analyzing other companies.

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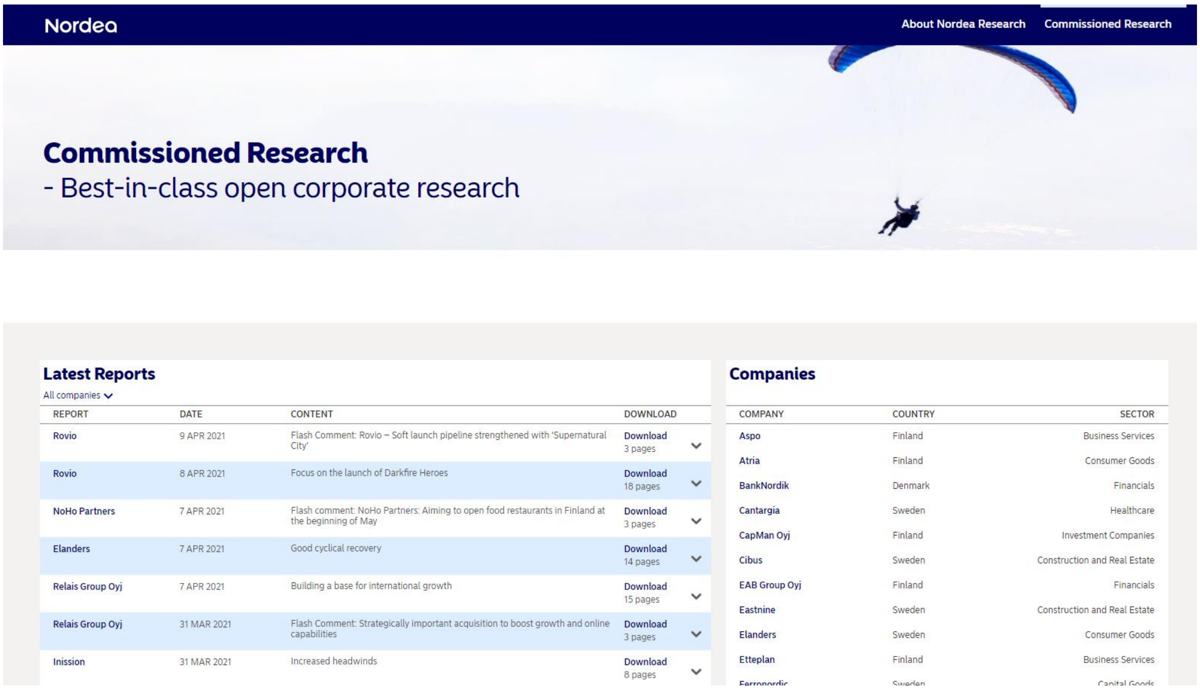
FigureA1. Nordea commissioned research website

This is one example of paid-for-research firm website. You can find the list of the paying companies and download the research reports for fee.



APPENDIX A. Detailed Sample Construction

First, to find brokers that operate both brokerage and paid-for-research business, I start with internet searches such as 'issuer-paying research', 'commissioned research', 'paid-for-research', or 'company-sponsored-research'. By visiting each website relevant to any of those key-words and getting the names of paid-for-research firms from prior literature (Kirk; 2011, Billings et al.; 2014.), I collected 40 research firms. Some of the firm names I collected in news articles and some are from the company's website. I find most of the paid-for-research firms used as a sample in previous literature do not exist now.

Next, I visited each research firm's website and see if they provide both types of research, paid-for-research and traditional sell-side research. Some of the companies provide paid-for-research as well as non-paid-for-research, but if they don't have the brokerage business, I excluded them from the universe. This process gives me three research houses; Nordea, AlphaValule, Exane BNP Paribas. Figure3 shows the homepage of Nordea commissioned research.

Next, I collect the list of paying companies from the website of these three brokers. Brokers provide the paid-for-research papers for free for a certain period, two to four years, depending on their contract with paying companies. I match these paying company names with I/B/E/S company name (CNAME) to find the analyst code (ANALYS) and broker code (ESTIMATOR). Then I double-confirm if the first I/B/E/S forecast estimates announcement date of the paying company matches the date of the paid-for-research initiation report. I don't include OTC companies. (Many OTC market companies hire paid-for-research to get exposed to investors.)

This process allows us to identify 32 analysts and 74 paying companies. These analysts work for sell-side brokers and provide equity research analysis for both paying companies and non-paying companies. Finally, I obtain the complete coverage list of these 32 analysts from I/B/E/S during 2017-2020 to construct the entire sample of non-paying firms' forecast estimates.

APPENDIX B. Variable Definitions

Variable	Definition
Dependent Variables	
Accuracy	The absolute value of actual earnings per share value in I/B/E/S minus the forecasted earnings per share (|FE|) scaled by price, a measure of forecast accuracy
Ind_Cvg	Industry Coverage. The number of firms that analyst *i* follows in the same sector of a company *j* at time *t*
Ind_Wgt	A measure of analyst *i*'s sector coverage density for the same sector with a company *j*. It is calculated as the number of coverages in the same sector with a company *j* divided by the total number of coverages of an analyst.
Independent Variables	
POST	POST indicates 1 if the earning estimate announced after the analyst starts to cover a paying company and 0 otherwise.
TREAT	TREAT indicates 1 if the company is in the same industry with the paying company and 0 otherwise.
$TREAT_{SMALL}$	TREAT × SMALL where SMALL is defined as 1 if market cap of a company *j* is below the median, 0 otherwise.
$TREAT_{LARGE}$	TREAT × LARGE where LARGE is defined as 1 if market cap of a company *j* is above the median, 0 otherwise.
Control Variables	
BTM	Book value of equity divided by the market value of equity from the company’s most recent annual financial statement
Size	Natural log of the market value of the company at the end of previous month
Following	Natural log of one plus the number of analysts following the company in the year for the I/B/E/S analyst forecast announcement report
Coverage	Natural log of one plus the number of total coverage of analyst *i*
Frequency	Natural log of one plus the number of forecast estimates for company *j* updated by analyst *i* at the year
FirmExp	A measure of analyst *i*'s firm-specific experience. Natural log of one plus the years of the analysts for following the firm *j* at the date *t*. The years of the analysts for following the firm *j* at the date *t* is calculated as the forecast earnings announcement date of the firm *j* minus the initiation date of the coverage divided by 365.
Exp	A measure of analyst *i*'s experience. Natural log of one plus the years of the analysts experience at the date *t*. The years of experience at the date *t* is calculated as the forecast earnings announcement date of the firm *j* minus the initiation date of the first coverage divided by 365.
Release	Number of days between the forecast and the earnings announcement

Table 1. Paid-for-analysts sample selection

This table presents the procedures on how I construct the sample. I collect full analyst forecast estimates of the three brokers that provide both paid-for-research and non-paid-for-research from I/B/E/S for the estimate data announced between January 2017- October 2020. As the focus of the study is non-paying firms, estimates for paying companies are removed. I remove the estimates made one year before or after the event of each paying company's coverage initiation. Lastly, the outliers identified by studentized residuals are removed for the regression to get the final sample of 3,482 estimates.

	n
Paid-for analyst forecast estimates for 2017-2020 in I/B/E/S	12,674
Less:	
Estimates for paying companies	(2,035)
Unreported actual EPS for Fiscal Year 2020	(2,759)
Missing Capital IQ price data	(321)
Estimates made one year before or after paying the company's initiation	(3,984)
Outliers	(93)
Final Sample	3,482

Table 2. Descriptive statistics of the paid-for-analysts This table presents the distribution and the descriptive statistics of paid-for-analysts in the sample. The total number of paying companies covered by these paid-for-analysts is 74 between January 2017- October 2020, but in the regression analysis, we remove the two analysts who cover 10 and 13 paying companies. Panel A reports the sample distribution of the paid-for-analysts in the sample. Panel B tabulates the firm-year-analyst descriptive statistics for paid-for-analysts in the sample. * The means of the number of paying companies per paid-for-analyst, Excluding the two analysts who cover 10 and 13 paying companies, respectively.

Variable	N	Mean	SD	P25	Median	P75
Market cap ($mn)	607	7,011	12,004	916	2,477	6,933
Coverage	607	18	9	12	16	22
Firm_Coverage	607	11	8	6	8	16
Frequency	607	5	3	3	5	8
Firm_Exp	607	4.5	5.2	0.5	2.8	7.1
Exp	607	12.1	9.3	2.9	11.6	20.2

Table 3. Sample description by companies

The table tabulates the sample description of observations by companies. Panel A presents the firm-year descriptive statistics for the paying companies and non-paying companies covered by paid-for-analysts in the sample. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively, based on two-tailed tests. *Analyst following* indicates the number of analysts who cover the company each year. *Analyst Forecast Frequency* is the number of analysts' forecast updates for each company in each calendar year. Panel B shows the distribution of sample firm-date observations by the industry for non-paying companies and paying companies, respectively. The presented classification follows Barth et al. (1998) 23 industry code. We use four different industry classifications in the analysis, including Barth, Fama-French 48 industry classification, GICS 4-digit, and SIC 2-digit classifications.

Panel A. Firm-year descriptive statistics for the paying companies and non-paying companies

		Paying companies	Non-paying companies	Diff.
n		72	577	t-value
Market cap ($mn)	Mean	299.1	7,185.9	4.79***
Book to market value	Mean	0.9	0.7	-2.06**
Analyst Following	Mean	3.6	11.5	8.57***
Analyst Forecast Frequency	Mean	3.7	5.4	5.16***

Panel B. Sample distribution of full sample observations by industry

(Barth et al. (1998) 23 industry Code)

	Non-Paying Companies		Paying Companies		Total	
	Freq.	**Percent**	**Freq.**	**Percent**	**Freq.**	**Percent**
Mining/Construction	326	9.36	20	4.34	346	8.78
Food	102	2.93	29	6.29	131	3.32
Textiles/Print/Publish	289	8.30	65	14.10	354	8.98
Chemicals	40	1.15	0	0.00	40	1.01
Pharmaceuticals	22	0.63	39	8.46	61	1.55
Extractive	62	1.78	0	0.00	62	1.57
Manf:Rubber/glass/etc	134	3.85	1	0.22	135	3.42
Manf:Metal	194	5.57	0	0.00	194	4.92
Manf:Machinery	175	5.03	0	0.00	175	4.44
Manf:ElectricalEqpt	127	3.65	0	0.00	127	3.22
Manf:TransportEqpt	56	1.61	0	0.00	56	1.42
Manf:Instruments	31	0.89	6	1.30	37	0.94
Manf:Misc.	30	0.86	0	0.00	30	0.76
Computers	233	6.69	83	18.00	316	8.01
Transportation	162	4.65	6	1.30	168	4.26
Utilities	80	2.30	2	0.43	82	2.08
Retail:Wholesale	186	5.34	30	6.51	216	5.48
Retail:Misc.	202	5.80	4	0.87	206	5.22
Retail:Restaurant	0	0.00	26	5.64	26	0.66
Financial	183	5.26	15	3.25	198	5.02
Insurance/RealEstate	604	17.35	118	25.60	722	18.31
Services	210	6.03	7	1.52	217	5.50
Miscellaneous	34	0.98	10	2.17	44	1.12
Total	3482	100.00	461	100.00	3943	100.00

Table 4. The effect of covering paying companies on the forecast accuracy of non-paying companies, the main result for H1

This table presents the difference-in-difference regression result of the main hypothesis, H1. *POST* indicates 1 if the paid-for-analyst' earning estimate for a non-paying company is announced after the analyst starts to cover a paying company and 0 otherwise. *TREAT* indicates 1 if the non-paying company is in the same industry of the paying company and 0 otherwise. The negative sign of the coefficient of *POST*TREAT* means that the forecast accuracy of non-paying companies in the same industry of the paying companies improves after the analysts initiate the coverage for the paying company. t-statistics are in the parentheses, and *, **, *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively, based on two-tailed tests. The definitions of the variables can be found in Appendix B.

		(1)	(2)	(3)
VARIABLES			Accuracy	
Main Variables				
	*POST*TREAT*	-0.003**		
		(-2.055)		
	POST	0.002**	0.001	
		(2.044)	(1.250)	
	TREAT	0.001		0.000
		(1.136)		(0.143)
Firm Control Variables				
	BTM	0.028***	0.028***	0.028***
		(9.469)	(9.524)	(9.551)
	Size	0.008***	0.008***	0.008***
		(3.636)	(3.565)	(3.533)
	Following	-0.000	0.000	0.000
		(-0.013)	(0.074)	(0.106)
Analyst Control Variables				
	Coverage	0.002	0.002	0.002
		(0.917)	(0.915)	(0.917)
	Frequency	0.004***	0.004***	0.004***
		(3.737)	(3.699)	(3.677)
	FirmExp	-0.002*	-0.001*	-0.001
		(-1.717)	(-1.656)	(-1.575)
	Exp	-0.003**	-0.003**	-0.003**
		(-2.294)	(-2.332)	(-2.240)
	Release	0.000***	0.000***	0.000***
		(6.115)	(6.108)	(5.992)
Constant		-0.073***	-0.072***	-0.072***
		(-3.659)	(-3.602)	(-3.593)
Fixed Effect		Firm/Year	Firm/Year	Firm/Year
Observations		3,482	3,482	3,482
R-squared		0.743	0.742	0.742
Adj. R-squared		0.721	0.721	0.721

Table 5. The effect of covering paying companies on the forecast accuracy of non-paying companies by information environment, the results for H2

This table tabulates the difference-in-difference regression result of the second hypothesis (H2) by information environment using the two proxies of firm size and management voluntary disclosure. Panel A presents the effect of covering paying companies for paid-for-analysts on their forecast accuracy of non-paying companies by firm size. The small size group includes the estimates for the small-cap companies whose market cap is below the median of the total firms. The large size group consists of the rest. Panel B presents the effect of covering paying companies for paid-for-analysts on their forecast accuracy of non-paying companies by voluntary management disclosure. Without management guidance group includes the paid-for-analysts' earning estimates for the companies that did not announce revenue guidance. With management guidance group includes the rest. *POST* indicates 1 if the paid-for-analyst' earning estimate for a non-paying company is announced after the analyst starts to cover a paying company and 0 otherwise. *TREAT* indicates 1 if the non-paying company is in the same industry of the paying company and 0 otherwise. The negative sign of the coefficient of *POST*TREAT* means that the forecast accuracy of non-paying companies in the same industry of the paying companies improves after the analysts initiate the coverage for the paying company. t-statistics are in the parentheses, and *, **, *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively, based on two-tailed tests. The definitions of the variables can be found in Appendix B.

Panel A. The effect of covering paying companies on the forecast accuracy of non-paying companies by firm size

	SMALL Size Group			Large Size Group		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Accuracy			Accuracy	
Main Variables						
*POST*TREAT*			-0.005**			-0.002
			(-2.214)			(-1.312)
POST	-0.001		0.000	0.003***		0.003***
	(-0.565)		(0.413)	(4.256)		(4.367)
TREAT		0.000	0.002		0.000	0.001
		(0.084)	(1.194)		(0.444)	(0.864)
Firm Control Variables						
BTM	0.005	0.005	0.005	0.028***	0.029***	0.028***
	(1.442)	(1.451)	(1.327)	(6.373)	(6.504)	(6.397)

Size	-0.005*	-0.005	-0.006*	0.008***	0.008***	0.009***
	(-1.662)	(-1.612)	(-1.727)	(2.818)	(2.872)	(2.905)
Following	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001
	(-0.595)	(-0.616)	(-0.714)	(-0.264)	(-0.223)	(-0.318)
Analyst Control Variables						
Coverage	-0.002	-0.002	-0.001	0.006***	0.006***	0.006***
	(-0.481)	(-0.485)	(-0.318)	(3.000)	(3.242)	(2.919)
Frequency	0.008***	0.008***	0.008***	0.005***	0.005***	0.005***
	(4.358)	(4.369)	(4.418)	(4.014)	(4.141)	(4.064)
FirmExp	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.436)	(-0.495)	(-0.439)	(-1.432)	(-1.082)	(-1.457)
Exp	-0.004*	-0.004*	-0.004*	-0.006***	-0.006***	-0.006***
	(-1.852)	(-1.894)	(-1.890)	(-4.216)	(-4.373)	(-4.217)
Release	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(6.346)	(6.408)	(6.372)	(5.779)	(5.118)	(5.796)
Constant	0.052**	0.051*	0.053**	-0.089***	-0.093***	-0.091***
	(1.994)	(1.959)	(2.019)	(-3.047)	(-3.158)	(-3.122)
Fixed Effect	Firm/Year	Firm/Year	Firm/Year	Firm/Year	Firm/Year	Firm/Year
Observations	2,018	2,018	2,018	1,414	1,414	1,414
R-squared	0.809	0.809	0.809	0.925	0.924	0.925
Adj. R-sqaured	0.793	0.793	0.793	0.916	0.914	0.916

Panel B. The effect of covering paying companies on the forecast accuracy of non-paying companies by voluntary disclosure

	Without Management guidance			With Management guidance		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Accuracy			Accuracy	
Main Variables						
*POST*TREAT*			-0.004**			0.001
			(-2.519)			(0.369)
POST	0.001*		0.002***	-0.002		-0.002
	(1.880)		(2.802)	(-1.167)		(-1.196)
TREAT		0.000	0.002		-0.000	-0.001
		(0.094)	(1.320)		(-0.064)	(-0.231)
Firm Control Variables						
BTM	0.032***	0.032***	0.032***	0.013***	0.013***	0.013***
	(8.448)	(8.501)	(8.321)	(2.836)	(2.775)	(2.825)
Size	0.012***	0.012***	0.012***	-0.006	-0.006	-0.006
	(4.465)	(4.395)	(4.488)	(-1.305)	(-1.369)	(-1.331)
Following	-0.002	-0.002	-0.003	0.006	0.006	0.006
	(-0.885)	(-0.875)	(-1.005)	(1.533)	(1.465)	(1.525)
Analyst Control Variables						
Coverage	0.006***	0.006***	0.006***	-0.007*	-0.007*	-0.007*
	(2.791)	(2.840)	(2.825)	(-1.944)	(-1.869)	(-1.936)
Frequency	0.002*	0.002*	0.003*	0.014***	0.014***	0.014***
	(1.847)	(1.874)	(1.901)	(5.386)	(5.637)	(5.333)
FirmExp	-0.000	-0.000	-0.000	-0.007***	-0.007***	-0.006***
	(-0.333)	(-0.183)	(-0.328)	(-2.892)	(-3.045)	(-2.812)
Exp	-0.004***	-0.004***	-0.004***	-0.002	-0.003	-0.002

	(-2.805)	(-2.734)	(-2.825)	(-1.016)	(-1.227)	(-1.015)
Release	0.000***	0.000***	0.000***	0.000	0.000	0.000
	(5.985)	(5.813)	(5.991)	(1.099)	(1.362)	(1.086)
Constant	-0.107***	-0.106***	-0.107***	0.054	0.057	0.048
	(-4.597)	(-4.565)	(-4.599)	(1.318)	(1.372)	(1.146)
Fixed Effect	Firm/Year	Firm/Year	Firm/Year	Firm/Year	Firm/Year	Firm/Year
Observations	2,569	2,569	2,569	913	913	913
R-squared	0.724	0.724	0.725	0.804	0.804	0.804
Adj. R-sqaured	0.704	0.703	0.704	0.779	0.779	0.779

Table 6. The effect of covering paying companies on the coverage of non-paying companies, the results for H3

This table presents the difference-in-difference regression result of the effect of covering paying companies for the paid-for-analysts on the coverage of non-paying companies. *Ind_Cvg*$_{ijt}$ (Industry Coverage) means that the number of firms analyst *i* follows in the same industry of a company *j* at time *t*. *Ind_Wgt*$_{ijt}$ is the ratio of the companies in the same industry of a covering company *j* divided by the total number of coverages of the analyst *i* at time *t*. *POST* indicates 1 if the paid-for-analyst' earning estimate for a non-paying company is announced after the analyst starts to cover a paying company and 0 otherwise. *TREAT* indicates 1 if the non-paying company is in the same industry of the paying company and 0 otherwise. The negative sign of the coefficient of *POST***TREAT* means that the forecast accuracy of non-paying companies in the same industry of the paying companies improves after the analysts initiate the coverage for the paying company. t-statistics are in the parentheses, and *, **, *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively, based on two-tailed tests. The definitions of the variables can be found in Appendix B.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		Ind_Cvg			Ind_Wgt	
Main Variables						
*POST*TREAT*	1.165***			0.072***		
	(7.287)			(7.629)		
POST	-0.140*	0.100		-0.015***	-0.001	
	(-1.730)	(1.287)		(-3.082)	(-0.119)	
TREAT	-0.187		0.659***	-0.012		0.040***
	(-1.280)		(7.242)	(-1.345)		(7.440)
Firm Control Variables						
BTM	0.251**	0.330***	0.287**	0.007	0.012	0.009
	(2.052)	(2.610)	(2.303)	(0.911)	(1.358)	(1.091)
Size	0.284**	0.289**	0.313**	-0.002	-0.000	0.001
	(2.020)	(1.987)	(2.190)	(-0.184)	(-0.049)	(0.113)
Following	-0.698***	-0.773***	-0.744***	-0.012	-0.015	-0.015
	(-3.812)	(-4.076)	(-3.996)	(-1.122)	(-1.403)	(-1.417)
Analyst Control Variables						
Coverage	3.033***	3.072***	3.085***	-0.075***	-0.075***	-0.074***

	(27.544)	(26.989)	(27.639)	(-10.677)	(-10.231)	(-10.325)
Frequency	0.076	0.098	0.097	0.011**	0.012***	0.012***
	(0.995)	(1.239)	(1.244)	(2.476)	(2.618)	(2.720)
FirmExp	0.019	0.077	0.050	0.018***	0.021***	0.019***
	(0.250)	(0.990)	(0.662)	(3.976)	(4.614)	(4.203)
Exp	-0.344***	-0.374***	-0.347***	-0.042***	-0.043***	-0.042***
	(-5.267)	(-5.523)	(-5.229)	(-10.660)	(-10.653)	(-10.620)
Release	-0.001*	-0.001	-0.001*	0.000	0.000*	0.000
	(-1.723)	(-1.638)	(-1.825)	(1.613)	(1.666)	(1.568)
Constant	-4.249***	-4.178***	-4.609***	0.562***	0.563***	0.540***
	(-4.095)	(-3.900)	(-4.369)	(9.088)	(8.801)	(8.579)
Fixed Effect	Firm/Year	Firm/Year	Firm/Year	Firm/Year	Firm/Year	Firm/Year
Observations	1,774	1,774	1,774	1,816	1,816	1,816
R-squared	0.838	0.826	0.832	0.777	0.760	0.768
Adj. R-sqaured	0.802	0.787	0.795	0.727	0.706	0.717