The London School of Economics and Political Science

Essays on financial analysts and broker-hosted conferences

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my work other than where I have clearly indicated that it is the work of others (in which case, the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorization does not, to the best of my belief, infringe the rights of any third party.

I confirm that Chapters 1 and 2 are jointly co-authored with Peter Pope (Bocconi University) and Ane Tamayo (LSE).

I declare that my thesis consists of 59,706 words.

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Abstract

This thesis consists of three chapters that explore sell-side analysts' attribute, the new regulation on them, and the research service provided by them on the capital market.

Chapter 1 (co-authored with Peter Pope and Ane Tamayo) studies the impact on sell-side analysts and the stock market of separating research payments from dealing commissions. We exploit an exogenous shock to sell-side analysts' research income in Sweden, caused by several of Sweden's largest asset managers' adoption of the unbundling model (the RPA model) to pay for the equity research purchased from the sell-side. Using a hand-collected dataset revealing analyst location, we find that the introduction of the RPA model coincides with a reduction in the supply of sell-side research services. The RPA model is associated with a reduction in analysts' coverage lists, with some firms losing analyst coverage. This reduction is greater for firms with lower institutional ownership and with lower market value of equity, as well as firms that are not in the Benchmark index. Moreover, we find that, after controlling for changes in analyst coverage, the adoption of the RPA model is associated with an overall improvement in analysts' research quality, as evidenced by superior earnings forecast ability in the post adoption period. Lastly, we find that the market reacts more strongly to forecast revisions in the post RPA adoption. Overall, our results suggest that unbundling research payment is associated with an improvement in the information environment for firms with analyst coverage, but some firms suffer a loss of analyst coverage.

In Chapter 2 (co-authored with Peter Pope and Ane Tamayo), we investigate the effects of broker-hosted credit conferences on the corporate bond market. We find that firms with a greater probability of financial distress, more public debt, and lower time-to-maturity of bonds are more likely to attend credit conferences. Next, we find that the bond market mainly reacts to credit conferences, rather than non-credit conferences. In addition, we document a greater market reaction to credit conferences when bonds have speculative grade credit rating and short time-to-maturity. Furthermore, we find that firms attending credit conferences experience a reduction in the cost of debt in the subsequent months. Lastly, we document an increase in

institutional investor ownership of bonds after the credit conference participation; this increase is mainly attributable to mutual fund investors. None of these results hold for non-credit conferences.

Finally, in Chapter 3 (solo-authored), I investigate the role of analysts' educational backgrounds in the analysis of R&D intensive firms within the chemical manufacturing industry. Firms' technological complexity has a negative impact upon analysts' behavior. Using R&D intensity as a proxy of technological complexity, and hand-collected data of analysts' educational degrees, I find that analysts with a matching technological degree cover less industries, and firms' analyst following by analysts with (without) a matching degree is positively (negatively) associated with firms' R&D intensity. Furthermore, I find that a matching technological degree that an analyst holds ameliorates the negative impact of the R&D intensity on analysts' forecast accuracy. Next, I find that the market reactions to upward recommendations revised by matching analysts are greater than that revised by non-matching analysts. Lastly, when restricting the sample to the group of pharmaceutical firms, I find a negative association between analysts' boldness and firms' R&D intensity; but when analysts have matching technological degrees this alleviates the negative association.

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Chapter 1

The impact of separating research payment from dealing commissions: Evidence from Sweden

1.1 Introduction

In January 2018, the European Union issued a new directive changing how asset managers pay for the research services provided by sell-side analysts. Previously, brokers bundled payments for research services with trade execution fees. However, due to the perceived inefficiencies that the bundled model creates, the new Directive states that payments for research and trading execution should be separate. In this paper, we study a new research payment regime in Sweden – the earliest implementer of the new payment method – to test the potential impact of brokerage fee unbundling. Specifically, we study the impact of the change to brokerage fee payments on the information environment, in the form of sell-side analysts' coverage and forecast accuracy.

The extant literature examining sell-side analysts' incentives when choosing firms to cover and when forecasting earnings and other outcomes concentrates on two sources of compensation for their research services: (1) subsidies from the investment banking department; and (2) the sharing of dealing commissions with brokerage houses' trading operations. One stream of the literature conjectures that a significant portion of analysts' research income is subsidized by the investment banking function within a brokerage house (Lin and McNichols 1998; O'Brien et al. 2005; Michaely and Womack 1999; Dechow et al. 2000). Another stream of papers investigates the impact of analysts' research income coming from dealing commissions when the brokerage house handles investors' trades (Hayes 1998; Irvine 2000; Irvine 2004; Jackson 2005; Cowen et al. 2006). When a brokerage house pays for services (or other perquisites) consumed by asset managers as a result of dealing commissions generated by the brokerage arrangement, this has become known as a "soft dollar" arrangement. Hence, providing "free" (or subsidized) research developed within the brokerage house and consumed by the asset manager is a form of soft dollar arrangement.

Soft dollar arrangements are potentially inefficient because they encourage over-consumption by asset managers at asset owners' expense as dealing commissions are higher than they need be. On the supply side, when they are not held accountable for the profitability of their own decisions, analysts have incentives to offer a "waterfront coverage" of firms, i.e., to cover as many firms as possible to solicit asset managers (Edison Investment Research 2013). Sell-side research is effectively an "advertising tool" to attract asset managers. Moreover, as analysts' research income is directly linked to the value (and the volume) of trades executed by brokerage houses under the bundled model, a higher amount of trading volume will generate higher dealing commissions (hence research income) to analysts, creating incentives for analysts to issue optimistically biased forecasts and recommendations. Profit-maximizing brokers required to charge asset managers for the supply of research services will have incentives to better control the supply of research, adjust supply in response to asset managers' demand and allowing the reduction of dealing commissions to the benefit of asset owners.

There is a paucity of empirical evidence on the role of sell-side research in determining dealing commissions, primarily due to lack of data on dealing commission components and the lack of time series variation in commission arrangements. In one of the handful of papers, Maber et al. (2014) use proprietary data to study 'broker votes', an important mechanism to allocate the research income among analysts. They find that brokerage houses use broker votes to indirectly reward analysts for the contribution they make to generating dealing commissions. We do not consider the compensation of individual analysts in this paper, but seek instead to exploit a rare change in the research payments system from the dealing commission to study how a change in compensation for research influences the supply of brokerage research services, with a focus on analysts' coverage decisions and the quality of their research.

Regulators have recently taken an interest in the possible inefficiencies of the bundled research payments system. The European Commission proposed in the Markets in Financial Instrument Directives II (MiFID II) that asset managers be required to establish a separate research payment account (RPA) to handle payments for research. Under the RPA approach, brokerage houses charge asset managers separately for dealing commissions and research payments. Asset managers have to decide whether to bear the costs of research on their own account or pass on the charges to asset owners. Either way, asset managers have incentives to consider carefully the amount they spend on sell-side research service. Hence, the RPA model can mitigate overspending on research services by asset managers. From sell-side analysts' viewpoint, the RPA model breaks the link between the trading volume and research payments. This renders a "waterfront coverage" style – covering a large number of firms – and potentially biased forecasts, unprofitable. As a result, analysts may reduce their coverage lists and provide higher quality research in an attempt to secure their share of research payments.

The European Union implemented MiFID II as recently as 3 January 2018, meaning that EU wide data to test implementation effects unavailable.[1] However, at the beginning of 2015, several of the largest and most influential Swedish asset managers announced that they had decided unilaterally to separate sell-side research payments from the dealing commission as an endorsement of the debate regarding the proposal to unbundle the research payment in MiFID II. The preemptive voluntary adoption of the RPA approach in Sweden provides an interesting setting to generate early insights into how the supply and quality of analysts' research changes in response to the research payment structure.

We predict that the implementation of the RPA payment model creates incentives for Swedish analysts to reduce coverage of firms where the demand for research is low and to improve the quality of the research they continue to perform. We use a difference-in-differences research design to study the supply of sell-side research by Swedish analysts, where the introduction of RPA in Sweden is likely to have greatest impact. As our starting point, we predict that the number of firms on analysts' coverage list falls with the adoption of RPA in Sweden. We hand-collect the geographical location of analysts covering firms listed on Swedish stock markets. We identify 1,582 analysts, including 223 Swedish analysts. After discarding four Swedish analysts who relocated internationally, we classify 219 Swedish analysts as the treated analysts, and 1,359 non-Swedish analysts as the control group to test the hypothesis within a difference-in-difference design. We find that Swedish analysts, compared to non-Swedish analysts, drop 0.62 firms after the adoption of the RPA

[1] Available at: https://www.esma.europa.eu/policy-rules/mifid-ii-and-mifir. [Accessed: 20 August 2017]

model. Secondly, we use firms that are listed on the largest Swedish stock market – Nasdaq OMX Stockholm as the sample, hypothesize and find that Swedish analysts primarily reduce coverage of firms with low institutional investor ownership and low market capitalization, as well as firms that are not included in the Benchmark index.[2] More precisely, after the adoption of RPA in Sweden, firms with low institutional investor holdings suffer a reduction of 0.22 analysts, compared to firms with high institutional investor holdings. In addition, the reduction in analyst coverage among small firms is 0.65 relative to large firms, equivalent to a 72% reduction in the mean of the number analysts following small firms. With regard to the firms that are not included in the Benchmark index, they experience 0.46 more analysts' reduction relative to the Benchmark index firms. Thirdly, we use analysts' forecast accuracy as the proxy of research quality to test the change in the research quality after the Swedish RPA adoption. Results show that analysts' forecast errors decrease by 0.33% after the introduction of the RPA model. We further find that the decrease in analysts' forecast error is due to the improvement in analysts' forecast ability, rather than the elimination of supply of forecast by lower quality analysts. Lastly, we find that the market reaction to analysts' forecast revisions increases by 40% with the RPA adoption.

Our paper makes the following contributions. Firstly, it makes the first contribution in the literature on the role of payments for research when bundled with dealing commissions. When studying the effect of the trading volume on analysts' behavior, the extant literature builds the research on the premise of a positive association between analysts' research income and the trading volume. We use a novel setting and study the change of analysts' coverage decision and research quality when this association disappears. Secondly, our paper contributes to the indirect effect of analysts' on the stock market. The change in the research payment structure has a direct impact on analyst coverage, with a reduction in the supply of research for firms with low institutional investor holdings and low market capitalization. Thirdly, we provide early empirical evidence to the newly implemented regulation in MiFID II in terms of the potential unintended consequences of separating research payments from dealing commissions.

[2] The Benchmark index refers to Nasdaq OMX Stockholm Benchmark index, which is the major index in Sweden. The Benchmark index only consists of the largest and the most liquid stocks.

The remainder of this study is organized as follows. In the next section, we provide a brief background for the research payment method, discuss the related literature, and develop the hypotheses. In Section 1.3, we outline the research design. Section 1.4 presents the various sources of data and gives a general description of the Swedish market. Section 1.5 reports the primary results and findings. Section 1.6 concludes.

1.2 Background, literature review, and hypothesis development

1.2.1 Background

Asset managers' payment for the sell-side research service is bundled with the trading execution fees under the head of dealing commissions. In the US, the "Safe Harbor" in the Section 28(e) of the Securities Exchange Act (SEA) of 1934 permits asset managers to pay a premium to brokers for additional services in the dealing commission when seeking brokerage services. The additional services may include software, hardware, database access and research reports issued by brokers' research departments. Although the Section 28(e) of SEA requires asset managers to disclose such arrangement, the disclosure can be opaque. Asset managers must disclose the total amount of dealing commissions and the existence of the soft dollar arrangement, but they do not necessarily report the exact amount of the payment for a research service. The reason that the SEC introduced Safe Harbor in the SEA is to protect asset managers from the potential breach of fiduciary duty. Without Safe Harbor, asset managers, in an attempt to avoid litigation by asset owners for breaching fiduciary duty, may be more likely to select brokerage services with the lowest commission fees, regardless of the quality of the service. However, use of soft dollar arrangements and the bundled research payments model is controversial. Advocates argue that soft dollars are an innovative and efficient form of economic organization that benefits investors (Johnsen 2009). Brennan and Chordia (1993) suggest that trading volume could be a proxy for information quality, and asset managers obtaining high quality information may achieve better gross performance. In contrast, the opponents of fee bundling argue that asset managers may abuse the opacity of soft dollars to unjustly enrich themselves (over-spending), leading to inefficient use of asset owners' resources (Blume 1993, Bolge 2009, Erzurumlu and Kotomin 2016).

The brokerage service industry in the EU is similar to the US. Payments for research service are bundled with trading execution fees, and charged to the investors as a whole package under dealing commission. The EU, endorsing the unjust enrichment argument that asset managers overspend on the sell-side research service by using investors' money, took the first step to unbundle research payments from dealing commissions in the recent implementation of the Markets in Financial Instruments Directive II.[3]

1.2.2 The Bundled Model

Figure 1.1 Panel (A) illustrates the bundled model graphically. Asset managers pay for the research service bundled together with the trading execution service under the head of dealing commissions, and then send the invoice for dealing commissions to their clients. The dealing commission is calculated as the trading value multiplied by a fixed rate negotiated between asset managers and brokers ex ante. Having received the dealing commission, brokerage houses split and distribute the commission in a fixed proportion to the research department where sell-side analysts work and the trading department.[4]

Academics, practitioners and regulators have discussed over years the merits and demerits of the bundled model and the so-called soft dollar arrangements, although a negative view seems to prevail. On the one hand, advocates of the bundled model argue that this payment regime is an innovative and efficient form of economic organization, which benefits investors as soft dollars efficiently subsidize asset managers' search for profitable trades (Horan and Johnsen 2000; Johnsen 2009). To the extent that sell-side analysts provide research insights to asset managers in advance of trading, the bundled payment model acts as an ex-ante effective bond that enhances the quality of research and brokerage execution services. As such, the bundled model mitigates agency problems inherent in delegated portfolio management. On the other hand, detractors of the bundled model maintain that the opaqueness of this method of payment may induce asset managers to unjustly enrich themselves at expense of asset owners, without bringing extra return for the fund (Bogle 2009; Blume 1993; Edelen et al. 2012; Erzurumlu and Kotomin 2016). Specifically, under the bundled model,

[3] Commission Delegated Directive (EU) 2017/593. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32017L0593&from=EN. [Accessed: January 20, 2017] Appendix 1.2 provides more details.

[4] The anecdotal evidence from one of the largest brokerage houses in London suggests that the percentages of the commission split are 55% to the research department and 45% to the trading department.

asset managers may treat sell-side research services as a “free good” because they do not bear the cost of consuming such service. Brokerage houses, in turn, may use their research services as an “advertising” tool to solicit business from asset managers. Given that the exact amount spent on research is unknown to investors, asset managers may prioritize this research service in the selection of trading execution services provided by brokerage houses (Myners 2001).[5]

Empirical evidence on this matter is relatively scarce. A few studies have examined whether soft dollar arrangements deliver superior returns to investors. In a recent paper using actual amounts of soft dollar research payments and total brokerage commissions carefully collected for a large number of funds, Erzurumlu and Kotomin (2016) show that higher soft dollar and total brokerage commissions are associated with higher advisory fees but not with higher risk-adjusted fund returns. In the same spirit, Edelen et al. (2012) compare the return performance in funds where the distribution cost is either bundled with brokerage commissions (relatively opaque) or expensed from funds’ income statement (relatively transparent). They find that the impact of the opaque distribution cost on fund return is significantly more negative than that of the transparent distribution cost. Although Edelen et al. (2012) focus on the distribution cost, rather than research payments, the opaqueness of brokerage commissions is associated with the poorer performance.

Additionally, the bundled model directly links analysts’ compensation to the trading value (or volume), which lays the cornerstone of the literature on analysts’ optimism and the trading commission. (Jackson 2005; Cowen et al. 2006; Ljungqvist et al. 2007). The value of trades executed determines analysts’ research income so that analysts issuing optimistic forecasts or recommendations could generate more trading commissions, and then more research income.

Around 2006, several countries started to modify the bundled model by suggesting alternative ways to distribute research payments among different brokers. In the US, SEC released guidance regarding the use of *Client Commission Arrangement* (CCA), whilst in the UK, Financial Service Authority (FSA, the predecessor of the current UK

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[5] Anecdotal evidence shows that asset managers are bombarded by research reports. Only a tiny portion of those reports are read by the asset managers. For example, ‘ …[A]sset managers are bombarded by 1.5 million report and only 5% may actually be read by their clients…’ Available at: http://www.economist.com/blogs/schumpeter/2014/05/regulating-equity-research. [Accessed: April 20, 2016]

financial regulator – Financial Conduct Authority) introduced the *Commission Sharing Agreement* (CSA).[6,7] Since CCA and CSA are almost identical, we focus on the CSA to describe the *modified bundled model*, depicted graphically in Panel (B) of Figure 1.1.[8]

Under the CSA, asset managers enter into an agreement to set up an account with their brokers wherein a separate portion of the dealing commission is preserved for the research service. The broker manages the account and distributes the research service payment through a process called "broker votes" to all sell-side research providers who have contributed to the trade. The analyst who has the greatest contribution receives the largest number of votes and then is accordingly allocated the largest portion of the research payment. Thus the research payment does not entirely flow to the broker who provides the trading execution service, which reduces analysts' incentives to provide optimistic opinions (Galanti and Vaubourg 2017).

CSA does not mitigate, however, the opaqueness of research payments in the dealing commission. First, dealing commissions (research payments together with trading execution fees) as a whole are determined by the trading volume. Second, asset owners would not know the precise amount spent on the research service. The over-spending of the sell-side research service continue to exist after the implementation of CSA.[9]

1.2.3 The Unbundled Model (RPA Model)

ESMA, the EU regulator imposes a strict separation between research payments and execution fees in the recently adopted MiFID II. The Article 13 of the Commission Delegated Directive (EU) 2017/593 specifies the following conditions where the sell-side research service can be provided "…if it is received in return for

a) direct payment by the investment firm out of its own resources;

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[6] SEC introduces Client Commission Arrangement on July 24, 2006. Available at: https://www.sec.gov/rules/interp/2006/34-54165.pdf [Access August 18, 2018]

[7] UK introduce Commission Sharing Agreement in July 2006. Available at: https://www.theinvestmentassociation.org/assets/files/research/2014/20140218-imadealingcommissionresearch.pdf. [Access October 20, 2015]

[8] One different aspect between CCA and CSA is that the participants in the CCA must be registered broker dealers, and cannot be the "introducing broker". Online available: http://www.integrity-research.com/ccas-versus-csas-when-is-a-commission-not-a-commission/ [Access August 19, 2018]

[9] According to the FSA (2012) survey, "…too few firms (funds) adequately controlled spending on research and execution services…" (Page 7).

b) payments from a separate research payment account controlled by the investment firm…" [10]

Thus, the precise amount of the research payment in the Research Payment Account (RPA), in line with trading execution fees, will be presented separately to investors (condition b). Panel (C) of Figure 1.1 illustrates the RPA model. Under the RPA model, the concepts of the dealing commission and the soft dollar arrangement disappear. The link between research payments and the trading volume does not exist anymore. Alternatively, asset managers can always choose to bear the cost of the research service themselves (condition a). Either asset managers self-financing or using RPA to pay for the research service will radically curb asset managers' overspending of the research service.

MiFID II has officially been implemented within the EU since January 3rd, 2018. However, influenced by the unbundling proposal in the MiFID II regulation in 2014, the Swedish Financial Supervisory Authority (Finansinspektionen – 'FI' hereafter) expressed strong preference for the complete separation of research payments from the dealing commission. FI had a long discussion with the fund management industry about the commission separation in 2014.[11] Furthermore, in the revised Swedish Code of Conduct for fund management companies issued in 2015 by the Swedish Investment Fund Association (SIFA), the SIFA members are required to separate research payments from the execution service cost.[12] [13] If a member does not comply with the code, this member must provide an explanation for the deviation.[14] Although

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[10] Commission Delegated Directive (EU) 2017/593. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32017L0593&from=EN. [Accessed: January 20, 2018] More details about Article 13 are presented in Appendix 1.2.

[11] Available at: http://www.fi.se/Tillsyn/Skrivelser/Listan/Hantering-av-analyskostnader-i-fonder/. This is the letter sent by the FI to the fund management industry about the importance of the rules about best execution and inducements which declares that the management company cannot charge extra fees unless it is in the customers' best interest. [Accessed: April 25, 2016]

[12] Swedish Investment Fund Association (Fondbolagens förening, SIFA hereafter) is an association for both Swedish investment funds and foreign funds which have Swedish subsidiaries or branches. It has collectively 42 members representing the majority of funds in Sweden (http://fondbolagen.se/en/About-us/).

[13] In the Code of Conduct, page 6, "…[c]osts for investment research may be charged with the fund only where the research enhances the quality of the fund management and the unit-holders have been duly informed. This requires that the benefit of the research is considered to correspond to the costs. The costs for research must be separated from the costs for execution of orders…" Appendix 1.3 presents more details. Available online: http://fondbolagen.se/en/Regulations/Guidelines/Code-of-conduct/

[14] In the Code of Conduct, page 2, "…For Swedish fund management companies, however, the intention are that deviations shall not be permitted when the word "must" is used. Members of the Swedish

the SIFA code does not explicitly specify using RPA to pay for the research service, the separation between the research service payment and the execution fee is, in spirit, equivalent to RPA. The burden of imposing the research payment separation varies across asset management companies. Compared to large asset management companies, adopting RPA would be more disadvantageous to small asset management companies for the following reasons. First, small asset managers have fewer resources of doing research than large asset managers. One way to level the playing field is to purchase the sell-side research service. The RPA model decreases the sell-side research purchase in general. The marginal impact of the decrease would be greater on the small asset managers who have fewer resources than large asset managers that possess abundant resources. Second, if asset managers choose to bear the cost of the research purchase by themselves, the research payment would have a greater influence on the small asset management companies with limited budgets on the research purchase. The research payment was previously bundled with the trading execution fees in Sweden. In 2015, some of the largest Swedish asset management companies announced the research payment separation, including Swedbank Robur, SEB and Svenska Handelsbanken.[15] These three asset management companies account for a 50% market share in the Swedish asset management market in terms of Assets under Management (AuM).[16] Their adoption provides exploitable data and a feasible setting, albeit containing noise, to study the impact of the RPA adoption on Swedish sell-side analysts and on the Swedish stock market as the early evidence to the newly implemented regulation in MiFID II in terms of the influence of separating research payments from the dealing commission.[17] [18]

Investment Fund Association must, in their Annual Reports or on their website, clearly state that they comply with the Code and must provide an explanation for any deviations."

[15] For example, Svenska Handelsbanken states the research payment separating on page 8 in the Information Brochure – Handelsbanken Fund AB, issued on January 12, 2016: "…As of January 1, 2015, expenses for external analyses will be charged separately. These expenses were previously included in the transaction costs. The expenses for external analyses will be included in the calculation of the annual fee…" Appendix 1.4 presents more details.

[16] The Riksbank (2014): The Swedish Financial Market 2014: Page 92, Table 14.

[17] The data is noisy because only three of the largest Swedish asset managers switched to RPA. Small asset managers may still use the bundled model. The same sell-side analysts could provide research service to both large and small asset managers. Therefore, separating sell-side analysts who are affected by the RPA from those who are not affected is less likely to achieve. More explanation will be given in the next section.

[18] For simplicity, we use RPA to replace the RPA-equivalent research payment method in the Swedish setting.

1.2.4 Identifying the treatment group and the control group.

As the largest Swedish asset managers have separated research payments from the dealing commission, we argue that Swedish brokerage houses and analysts are more likely to be affected. Thus we classify Swedish analysts as the treated analysts and non-Swedish analysts as the control group. However, both groups under such identification contains noise that cannot be removed. On the one hand, we should bear in mind that asset managers, rather than sell-side analysts, are subject to the RPA model in that the objective of the RPA rule in the MiFID II is to enhance the efficiency of asset managers using the research budget, alleviate the concern about the inducement, and then mitigate the over-spending of the research service. Therefore, even though some of the Swedish asset managers adopt the RPA model, Swedish brokerage houses are not restrained from accepting research payments from asset managers who do not use RPA (small Swedish asset managers and non-Swedish asset managers continue using the old bundled model in 2015). As one analyst can provide research services to and her brokerage house can receive payment from asset managers either using RPA or bundling it up with the execution service, separating out the analysts whose brokerage houses only receive research payments through RPA is less likely to achieve. As a result, the treatment group contains noise. On the other hand, the control group may contain noise as well. Swedish asset managers invest globally, meaning that Swedish asset managers in theory need the research services of foreign firms. Then they may pay foreign brokerage houses through the RPA method when they access the international market.[19] Figure 1.2 depicts the treatment group, the control group and the source of the noise in each group. The three largest RPA-adopting Swedish asset management companies create an exogenous shock to brokerage fees (the top box in the first column). Swedish brokerage houses that receive research payments from these three are affected by the RPA adoption, which are in the treatment group (Arrow 1). Foreign brokerage houses receiving research payments from foreign asset managers are then in the control group (Arrow 5). When foreign brokerage houses receive research payments from the three RPA adopting asset managers, it becomes the noise to the control group (Arrow 4). In the treatment group, the noise comes from foreign institutional investors (Arrow 3) and other Swedish asset

[19] In the anecdotal evidence (an email from asset managers in SEB), Swedish asset managers do purchase from international brokers but that mainly happens when they need to access the international markets.

managers that do not adopt the RPA model (Arrow 2). Despite the noise born with the identification, we are confident of the power of the setting (the solid arrows). Firstly, we believe that sell-side analysts would mainly serve the domestic asset managers rather than the foreign analysts.[20] Thus, the noise in the treatment group from foreign investors (Arrow 3) and the noise in the control group from Swedish asset managers (Arrow 4) would be trivial. Secondly, in terms of the noise in the treatment group from other Swedish asset management companies that do not adopt RPA (Arrow 2), we believe that the noise would be overwhelmed by the significant market power of the three RPA adopting asset managers.

In addition, the heterogeneity of the treated and controlled analysts' firm coverage may pose a threat to the parallel trend assumption. We argue that analysts mainly cover their domestic firms. In the treatment group, firms are mainly Swedish firms. In the control group, firms have a variety of origins, depending on the location of the analysts covering them. In this regard, although there may be a small group of firms covered by both Swedish analysts and non-Swedish analysts (the C area in Figure 1.3), the majority of firms in the treatment group are different to firms in the control group.

1.2.5 Hypotheses development

We develop our hypotheses with the understanding of the distinctive features among different payment models and regulators' motivation to shift the bundled model to RPA. The adoption of RPA leads to the curtailment of asset managers' research payments, creating an exogenous shock to brokerage fees, of which a significant portion is distributed to the research department as sell-side analysts' compensation. We expect that the reduced research payments affects analysts' coverage decision and their research quality.

(A) Analysts' coverage decision

We hypothesize that analysts reduce the number of firms in their coverage list with the RPA adoption. Asset managers are obliged to act in the best interests of clients when seeking brokers for the trade execution (Baker and Veit 1998; Game and Gregoriou 2014). Most of the brokers provide not only the trade execution service but also the research service. Asset managers are supposed to assess the quality of the

[20] In the anecdotal evidence (an email from one of the RPA adopting Swedish asset managers), Swedish analysts are the main research providers to Swedish asset managers.

entire package of the service provided by candidate brokers. Under the bundled model, research payments hide behind the mask of the dealing commission, which fends off the enquiries from the investors concerning the spending on the purchase of the research service. In this regard, the research service may induce asset managers to prioritize the research service over the trade execution service. Goldstein et al. (2009) find that institutional investors tend to concentrate order flows with a few brokers in an attempt to receive extra premium service. On the other hand, sell-side analysts would solicit asset managers by providing a wealth of research service that covers a wide range of stocks (waterfront coverage). Hence both the supply side and the demand side drive the over-production and over-consumption of the research service. However, bombarded by a myriad of research reports, asset managers are unlikely to use all of them, which leads to, from the stance of regulators, a severe waste of investors' money.[21] When switching to the RPA model, the research service will be priced independently based on the quality of the research service and the demand from the buy-side. Thus, the specific amount of research payments becomes transparent to investors. Under the investors' monitoring, asset managers may not be able to consume as much research service as under the bundled model. On this account, with the decrease in research consumption analysts will reduce the research cost accordingly. One of the feasible ways to cut the cost is to stop covering firms that are less likely to bring the research income under the RPA model.

Hypothesis 1: The adoption of RPA reduces the number of firms in analysts' coverage list.

(B) The type of firms being dropped

We expect that analysts under the RPA model selectively remove firms from their coverage list. More specifically, we argue that analysts are more likely to drop the firms whose research are less likely to attract asset managers to purchase under the RPA model. Under the bundled model, sell-side analysts cover a wide range of firms in an attempt to use the "quantity" to solicit asset managers. The cost for covering a company whose research have little use to asset managers is in a sense subsidized by covering other companies' research that is valuable to asset managers. Turning to the

[21] ' …[A]sset managers are bombarded by 1.5 million reports and only 5% may actually be read…' Available at: http://www.economist.com/blogs/schumpeter/2014/05/regulating-equity-research. [Accessed: August 25, 2015]

RPA model, asset managers seek and pay for the research service as well as the trading execution service separately. The separation and transparency of research payments and trading execution fees would lead to asset managers stopping spending on the research of firms that they have little investment intentions towards. Accordingly, sell-side analysts are more likely to drop the coverage of such firms. To test this hypothesis, we firstly use firms' institutional investor ownership as the directive measure of firms' attractiveness to asset managers. Then we expect that firms with low institutional investor holdings are less attractive to asset managers and experience a greater reduction in analyst following in the post period of the RPA adoption. Secondly, we use the firm size as another proxy of asset managers' investment intention, as institutional investors in general prefer to invest in large firms. In this regard, we expect that small firms in the post-RPA adoption period experience a greater reduction in analyst following than large firms. Thirdly, we use Nasdaq OMX Stockholm Benchmark index (Benchmark index hereafter) composite as the cutoff, and expect that firms that are not included in the Benchmark index are losing more analysts than firms in the Benchmark index.[22] Firms in the Nasdaq OMX Stockholm Benchmark index are the largest and the most liquid in the Swedish market, and we argue these firms are the more likely to attract to asset managers, which leads to have higher demand of analysts' research. The hypotheses are as follows:

Hypothesis 2a: After the RPA adoption, the decrease in the number of analysts following the firms with low institutional investor ownership is greater than firms with high institutional investor ownership.

Hypothesis 2b: After the RPA adoption, the decrease in the number of analysts following small firms is greater than large firms.

Hypothesis 2c: After the RPA adoption, the decrease in the number of analysts following the firms that are not included in Nasdaq OMX Stockholm Benchmark index is greater than the firms in the Benchmark index.

(C) Analysts' research quality

[22] Nasdaq OMX Stockholm Benchmark index "…consists of a selection of the largest and most traded stocks, with representation from a majority of the supersectors… especially attractive for use in different investment products and as a comparative index for investors…" Available at: https://indexes.nasdaqomx.com/Index/Overview/OMXSBGI [Accessed: July 28, 2018]

We predict that the adoption of the RPA model improves the sell-side research quality on average. Firstly, the RPA model increases competitiveness of analysts' labor market. In light of the regulator's objective of proposing RPA, brokerage fees are expected to decrease, and they flow more efficiently to analysts with ability to produce high-quality research. Low-quality research will be forced out of the market gradually. The overall sell-side research market will, accordingly, develop to a high degree of quality. Secondly, the RPA model breaks the link between analysts' income and trading volume, which in turn ameliorates their trading incentive to issue upward biased forecasts and recommendations. Analysts' incentive for issuing optimistically biased opinion has been widely studied. Bradshaw (2011) summarizes six sources that may lead to analysts' upward biased behavior. One of the incentives is trade generation.[23] Under the bundled model, analysts may issue upward biased forecasts and recommendations to inflate trading volume for their brokerage house, thus to generate higher research income from the dealing commission (Jackson 2005; Cowen et al. 2006; Ljungqvist et al. 2007). As the RPA model changes the way that analysts are compensated, analysts will not be rewarded by bringing more trades to their brokerage houses because the research service becomes a distinct product rather than a by-product that come with the execution service. On this account, analysts are compensated by providing high-quality research rather than by offering deliberately biased forecasts or recommendations.

We use forecast accuracy as the proxy to test the improvement in research quality.[24] The reasons are as follows. Firstly, forecast accuracy affects analysts' employment turnover. Analysts who constantly provide less accurate forecasts are more likely to leave the industry, which implies that the equity research market screens analysts' quality by forecast accuracy (Groysberg et al. 2011). Secondly, forecast accuracy remains one of the crucial qualities demanded by asset managers. In Brown et al. (2015), the authors survey 365 sell-side analysts and find that forecast accuracy remains important because analysts' clients (asset managers) demand it, as well as forecasts are the input to the stock recommendations that are highly valued by asset

[23] The other five sources in Bradshaw (2011) include boosting investment banking fees, currying favor with management, institutional investor relationship, research for hire, and analysts' cognitive bias.
[24] We use forecast accuracy and forecast error interchangeably. High forecast accuracy means low forecast error.

managers.[25] Therefore, forecast accuracy is appropriate to be a proxy of research quality. Our third hypothesis is as follows:

Hypothesis 3: Analysts' forecast accuracy improves after the adoption of RPA.

Now we turn to investigate how analysts improve their forecast accuracy in the post RPA adoption period. We posit two possible channels. Firstly, within the context of the reduced brokerage fees, increased competition in the equity research industry and the weakened incentive for issuing biased opinions, analysts that continue operating in the industry will make a great effort to improve their research quality to secure their jobs. Secondly, analysts may stop covering firms that they are unable to provide good forecast research on. Analysts may have the edge in covering certain firms but not in others. For example, some analysts may have private connections with some firms' management, which would facilitate high-quality research production (Chen and Matsumoto 2006; Brown et al. 2015). As low-quality research becomes a pure loss after asset managers switch to the RPA model, the likelihood of ceasing to cover firms on which they cannot produce high-quality research will be higher among analysts that are influenced by the RPA adoption than unaffected analysts. In this case, analysts do not improve their forecasting ability as discussed in the previous channel, but drop the firms that are hard to analyze. These possible channels are not mutually exclusive. All the forces could drive the quality of the equity research industry to a higher level. Our next hypothesis is therefore as follows:

Hypothesis 4a: The improvement in forecast accuracy in the post-RPA period is due to analysts improving their forecast ability.

Hypothesis 4b: The improvement in forecast accuracy in the post-RPA period is due to analysts ceasing to cover the firms for whom they are unable to provide high-quality research.

(D) Market reaction to analysts' forecast revisions

We hypothesize that the market reaction to analysts' forecast revisions increases with the RPA adoption. First, firms continue to be covered by analysts would experience an increase in analysts' forecast accuracy, as suggested in Hypothesis 3. Previous literature has documented a positive association between analysts' forecast

[25] Brown et al. (2015): page 31-34, Table 10.

accuracy and the market reaction to the forecast revisions (Abarbanell et al. 1995; Stickel 1992; Park and Stice 2000; Gleason and Lee 2003). Therefore, we expect that the market may react more strongly to the forecast revisions for firms that continue to be followed by analysts.

Second, for firms losing analyst coverage, we argue that the market may also react more strongly to the forecast revisions in the post period. The reduction in analyst following may lead to a deterioration of firms' information environment. Accordingly, investors may rely more on the remaining analysts as they have fewer information sources than that in the pre-RPA period. In this case, the market would react more strongly to forecasts revised by the remaining analysts. Both arguments support a greater market reaction to forecast revisions in the post RPA period. Then our hypothesis is as follows:

Hypothesis 5: The market reacts more strongly to analysts' forecast revisions in the post RPA adoption period.

1.3 Research design

1.3.1 Analysts' coverage list shortening

We use a difference-in-difference technique to test Hypothesis 1 within the sample period from 2013 to 2016. The dependent variable is the number of firms followed by each individual analyst within a quarter (*NUMCOM*). As the three largest Swedish asset management companies switched to RPA since 2015, we define an indicator variable, *RPA*, with the value of one for the years of 2015 and 2016, and zero otherwise. Furthermore, we define another indicator variable, *SW*, as the treatment variable, one for Swedish analysts and zero for non-Swedish analysts. Thus, the interaction term, $RPA \times SW$, captures the change in the number of firms followed by Swedish analysts relative to non-Swedish analysts after the RPA adoption in Sweden. We include a set of analyst-related control variables. Firstly, we add two control variables in line with Clement (1999): analysts' general experience (*GEXP*), defined as the number of years since the analyst provided her first forecast for any firm; and analysts' industry coverage (*NUMIND*), defined as the number of industries followed by each analyst.[26] We expect positive coefficients for both of these control variables because more experienced analysts are expected to follow more firms, and covering more industries may suggest more firms need to be added to analysts' coverage list. Secondly, Groysberg et al. (2011) find that analysts' forecast accuracy is positively associated with their employment turnover. In other words, analysts that cannot provide accurate forecasts have a higher chance of being fired. This is an extreme case of the reduction in the number of firms in analysts' coverage list. In an attempt to control for the ability of analysts' past accuracy (*PACY*), we following the method from Hong and Kubik (2003), according to which we calculate each individual analyst's average forecast accuracy score for the previous year in the following equations:

$$Percentile\ Rank_{ijt-1} = 100 - \frac{Rank_{ijt-1} - 1}{AAF_{it-1} - 1} \times 100 \tag{1.1}$$

$$PACY_{jt} = \frac{1}{n}\sum_{i}^{n} Percentile\ Rank_{ijt-1} \tag{1.2}$$

In the above equations, $Rank_{ijt-1}$ is the rank of analyst *j*'s forecast on firm *i* in year *t-1* relative to other analysts who also cover firm *i*.[27] AAF_{it-1} is the number of analysts following firm *i* in year *t-1*. $PACY_{jt}$ is the analyst *j*'s average accuracy scores in year *t-1*. Lastly, we also control for the brokerage house, analyst, and quarter fixed effects (*FE*) in different specifications to account for brokerage houses, analysts, and time unobservable invariants.[28] The regression is as follows:

$$\begin{aligned} NUMCOM_{jt} = {} & \alpha_0 + \alpha_1 RPA_t + \alpha_2 SW_j + \alpha_3 RPA_t \times SW_j \\ & + \alpha_4 GEXP_{jt} + \alpha_5 NUMIND_{jt} + \alpha_6 PACY_{jt} + FE + \varepsilon_{jt} \end{aligned} \tag{1.3}$$

[26] We use the first two digits of the SIC code to define industry. When we merge the data from I/B/E/S and from Compustat Global, only 75.5% number of firms are matched and have been found their SIC codes. Thus the variable *NUMIND* is underestimated.

[27] This is the only place where we use *t* as the year subscript. In the rest of this paper, the subscript *t* represents the time of quarters.

[28] We did not use I/B/E/S broker codes (ESTIMID) to create brokerage house dummy variables because they change when one brokerage house is acquired by another one. Thus, we obtain information of the brokerage houses from analysts' LinkedIn profiles and Bloomberg. Furthermore, subsidiaries of the same brokerage house in different countries share the same broker code. For example, both US Barclays and UK Barclays have the same I/B/E/S broker code "FRCLAYSC". We should treat US Barclays and UK Barclays as two different brokerage houses as analysts work in each firm are less likely to be affected by each other. Therefore, the brokerage house fixed effect includes analysts' location. For example, we have a dummy variable to US Barclays and a different dummy variable for UK Barclays.

1.3.2 Selective reduction in firms' analyst following

To test whether the reduction in analyst following for firms whose research are less demanded is more pronounced, we switch the unit of analysis from analyst-quarter (*j*, *t*) to firm-quarter (*i*, *t*). This firm-quarter unit of data structure allows us to incorporate firms' feature into the regression. We focus only on firms listed on the largest Swedish market (Nasdaq OMX Stockholm) and covered by Swedish analysts. The reasons are as follows. Firstly, elaborating on Hypothesis 1, Swedish analysts are the major influenced party to the RPA adoption, so that we focus on Swedish analyst following only. Secondly, firms listed on the other Swedish stock exchanges are too small and most of them are not followed by any analysts, so that we only use firms listed on the largest Swedish stock exchange, where the RPA adoption effect seem to be the greatest.

We use the Ordinary Least Square regression (OLS) to test Hypotheses 2a, 2b and 2c. The dependent variable is the number of Swedish analyst following each firm (*SW_AF*). The indicator variable *RPA* is the variable of interest as defined previously. Next, we define three dummy variables (***PROXY***) as the proxy for firms whose research are less demanded. First, we define dummy variable of *INSTLOW* as the low institutional investor ownership, set the value to one if a firm's institutional investor ownership is less than the median value of all firms at end of the last quarter in 2014, which is just before the PRA adoption in Sweden, and zero otherwise. In a similar vein, we define the dummy variable for small firms (*SMALL*) with the value of one if a firm has the market value of equity less than the median value of all firms before RPA was implemented in Sweden. In addition, we define dummy variable *NOBENCH* as the firm that are not included in the Nasdaq OMX Stockholm Benchmark index at the end of 2014. Therefore, the vector ***PROXY*** contains *INSTLOW*, *SMALL*, and *NOBENCH*. We interact ***PROXY*** with *RPA* to test the impact of the RPA adoption on the firms whose research are less demanded by asset managers. In line with the literature (Bhushan 1989; O'Brien and Bhushan 1990; Lang and Lundholm 1996; Liu 2011; Frankel et al. 2006; Barth et al. 2001), we include a set of control variables to account for factors that are associated with firms' analyst following: the market value of equity in the logarithm form (*MV*), stock return volatility (*RETVOL*), correlation between the stock return and the market return (*RSQ*), the market-to-book ratio (*MB*), the percentage of institutional ownership (*INST*), and total intangible assets scaled by total assets (*INTA*), as well as firm and quarter fixed effects in different specifications. The model is shown as follows:

$$\begin{aligned} SW\_AF_{it} = {} & \alpha_0 + \alpha_1 RPA_t + \alpha_2 \boldsymbol{PROXY_{it}} + \alpha_3 RPA_t \times \boldsymbol{PROXY_{it}} \\ & + \alpha_4 MV_{it} + \alpha_5 INTA_{it} + \alpha_6 MB_{it} + \alpha_7 INST_{it} \\ & + \alpha_8 RETVOL_{it} + \alpha_9 RSQ_{it} + FE + \varepsilon_{it} \end{aligned} \tag{1.4}$$

where ***PROXY*** *are INSTLOW, SMALL or NOBENCH*

The concern in this setting is the lack of the treatment/control structure. In an attempt to mitigate the endogeneity concern, we did a placebo test by shifting the RPA adoption dummy one-year prior to the actual adoption date. Specifically, we create an indicator variable – *PRE*, equal to one for the quarters after 2013Q4, and zero otherwise, we include both *PRE*, *RPA* and their interaction terms with ***RPOXY*** in the regressions (1.4), and expect no significance on the interaction terms of $PRE \times \boldsymbol{PROXY}$.

$$\begin{aligned} SW\_AF_{it} = {} & \alpha_0 + \alpha_1 PRE_t + \alpha_2 RPA_t + \alpha_3 \boldsymbol{PROXY_{it}} + \alpha_4 PRE_t \\ & \times \boldsymbol{PROXY_{it}} + \alpha_5 RPA_t \times \boldsymbol{PROXY_{it}} + \alpha_6 MV_{it} \\ & + \alpha_7 INTA_{it} + \alpha_8 MB_{it} + \alpha_9 INST_{it} + \alpha_{10} RETVOL_{it} \\ & + \alpha_{11} RSQ_{it} + FE + \varepsilon_{it} \end{aligned} \tag{1.5}$$

1.3.3 Analysts' research quality

Turning to the test of analysts' research quality, we use the difference-in-difference design again. The dependent variable is forecast error – *FORERR*, defined as the absolute value of the difference between the annual EPS forecast and the actual EPS value, deflated by the stock price two days before the forecast is provided. Then greater forecast error means lower research quality. The test has three dimensions: firm, analyst, and quarter (*i, j, t*). Two indicator variables, *RPA* and *SW*, are as previously defined, representing the post-RPA adoption period in Sweden and Swedish analysts when the values are equal to one. Then the interaction term $RPA \times SW$ captures the difference in the forecast accuracy improvement between Swedish analysts and non-Swedish analysts after RPA is adopted in Sweden. We control for a set of analyst-related and firm-related variables to alleviate potential omitted variable bias. Most of them have been previously defined. Firstly, in line with Clement (1999) and Mikhail et al. (1997), we control for firm-specific experience (*FEXP*) general experience (*GEXP*), the number of firms covered (*NUMCOM*) and the number of industries followed (*NUMIND*) by each individual analyst. Secondly, in an attempt to measure an individual analyst's past forecast ability, we use the past accuracy score (*PACY*) again. The last analyst-related control variable is forecast horizon (*HOR*), consistent with the finding in Brown (2001) that forecast accuracy improves with the revelation of information as the actual EPS announcement date approaches. We also add a range of firm-level variables to the regression, including the market value of equity in the logarithm form (*MV*), the total number of analysts following a firm (*AF*), the percentage of institutional ownership (*INST*), total intangible assets deflated by total assets (*INTA*), the market-to-book ratio (*MB*), and return volatility (*RETVOL*) (Alford and Berger, 1999; Brown, 1997; Sinha et al., 1997 etc.). Furthermore, in Brown (2001) and Hwang et al. (1996), they find that analysts have larger forecast error if firms report losses or have a declined actual EPS compared to the previous year. Then we include a dummy variable (*LOSS*) equal to one when the actual EPS is negative, and zero otherwise; as well as another dummy variable (*DECL*) equal to one when the actual EPS is less than that in the previous year, and zero otherwise. Lastly, we include firm, quarter and analyst fixed effects (*FE*) in different specifications to control for invariant factors. Based on the above discussion, we have the following research design:

$$\begin{aligned} FORERR_{ijt} = \alpha_0 + \alpha_1 RPA_t + \alpha_2 SW_j + \alpha_3 RPA_t \times SW_j \\ + \boldsymbol{\beta CONTROL_A} + \boldsymbol{\gamma CONTROL_F} + FE + \varepsilon_{ijt} \end{aligned} \tag{1.6}$$

where $\boldsymbol{CONTROL_A}$ is the analyst-level control variable vector:

– $GEXP_{jt}, FEXP_{ijt}, NUMIND_{jt}, NUMCOM_{jt}, PACY_{jt}, HOR_{ijt}$

$\boldsymbol{CONTROL_F}$ is the firm-level control variable vector:

– $MV_{it}, INTA_{it}, MB_{it}, INST_{it}, RETVOL_{it}, LOSS_{it}, DECL_{it}$

Next, we test which channel drives the increase in analysts' research quality (Hypothesis 4a and 4b). Firstly, to test Hypothesis 4a, we restrict the sample to analyst-firm pairs appearing both before and after the RPA adoption, and replicate the regression with analyst-firm fixed effects within the restricted subsample. Secondly, to test Hypothesis 4b, we create an indicator variable – *DIS*, which equals to one if analyst-firm pairs appeared in the pre-RPA period but disappeared in the post-RPA period, and zero otherwise. We run a logit model with *DIS* as the dependent variable in the pre-RPA adoption period. If the Hypothesis 4b is as predicted, we shall observe a positively significant on $SW \times FORERR$. The interpretation is that Swedish analysts are more likely to remove firms from their coverage list in the post-RPA period if they are unable to provide high quality forecasts for the firm, relative to non-Swedish analysts. The regression is as follows.

$$\begin{aligned}\Pr\left(DIS_{ijt} = 1\right) \\ &= \alpha_0 + \alpha_1 SW_j + \alpha_2 FORERR_{ijt} + \alpha_3 SW_j \times FORERR_{ijt} \\ &+ \boldsymbol{\beta CONTROL_A} + \boldsymbol{\gamma CONTROL_F} + FE + \varepsilon_{ijt} \qquad (1.7)\end{aligned}$$

1.3.4 Market reaction to analysts' forecast revisions

In this section, we use the size-adjusted absolute abnormal return as the proxy of market reaction to test Hypothesis 5. We conduct the analysis on the firm-day level for Swedish firms that are followed by at least one analyst. The dependent variable, *ABS_ABRET*, is the size-adjusted absolute abnormal return. To calculate the size-adjusted absolute abnormal return, we firstly find the quarter-end firm composite in the Nasdaq OMX Stockholm large-cap, medium-cap, and small-cap indices from Bloomberg, as well as the corresponding index returns. [29] Then we take the absolute value of the difference between firms' daily return and the daily OMX Stockholm large-cap index return if the firm is the included in the large-cap index, and convert it to the percentage form.[30] We replicate this step for the medium-cap firms and the small-cap firms respectively. The variables of interest are *RPA* (as defined previously) and *ANALYST*, which is an indicator variable with the value of one for the two-day [0, +1] window when analysts revise their forecasts for firms' quarter or annual earnings. We interact *ANALYST* with *RPA*, and expect a positive coefficient on the interaction term. Analysts providing forecast revisions are clustered with firms' earnings announcement (Keskek et al. 2014). We control for the confounding effect of the earnings announcement by including an indicator variable, *EARN*, for the two-day window [0, +1] when firms announce quarter or annual earnings. We also interact

[29] The OMX Stockholm large-cap, medium-cap, and small-cap indices are stock market indices for the Nasdaq OMX Stockholm exchange. The large-cap index includes companies with the market value of 1 billion euros or more. The medium-cap index captures the current status and changes in the Stockholm Mid Cap market. The small-cap index consists of companies whose shares have a market value of less than 150 million euro. Online available: https://indexes.nasdaqomx.com/Index/Directory/Stockholm. [Accessed 25 August 2018]

[30] The large-cap index value are not available before May 21, 2013 on Bloomberg or DataStream. Hence, the size-adjusted absolute abnormal return for large-cap firms starts from 22 May, 2013.

EARN with *RPA* to capture the potential impact of RPA on the informativeness of earnings announcement. We control for firm, day, and firm times quarter fixed effects (*FE*) in the different specifications.

$$\begin{aligned} ABS\_ABRET_{it} = \alpha_0 + \alpha_1 ANALYST_{it} + \alpha_2 ANALYST_{it} \times RPA_t \\ + \alpha_3 EARN_{it} \times RPA_t + \alpha_4 RPA_t + FE + \varepsilon_{it} \end{aligned} \quad (1.8)$$

The regression is on the firm-day level and does not the analyst dimension, meaning that this setting has the same endogeneity issue like Section 3.2. In an attempt to mitigate the endogeneity concern, we did a placebo test similar to Section 3.2. Specifically, we create an indicator variable – *PRE*, equal to one for the quarters after 2013Q4, and zero otherwise, we include both *PRE*, *RPA* and their interaction terms with *ANALYST* or *EARN*.

$$\begin{aligned} ABS\_ABRET_{it} = \alpha_0 + \alpha_1 ANALYST_{it} + \alpha_2 ANALYST_{it} \times RPA_t \\ + \alpha_3 EARN_{it} \times RPA_t + \alpha_4 RPA_t + \alpha_5 ANALYST_{it} \times PRE_t \\ + \alpha_6 EARN_{it} \times PRE_t + \alpha_7 PRE_t + FE + \varepsilon_{it} \end{aligned} \quad (1.9)$$

1.4 Data Collection

1.4.1 Collection of analysts' biographical information

The sample period is from 2013 to 2016 and data is collected quarterly. Swedish analysts are the variable of interest. However, we do not have a straightforward database providing analysts' biographical and geographical information.[31] Therefore we hand-collected the data. The steps are as follows and Table 1.1 Panel (A) reports the statistics:

1) We assume that the majority of Swedish analysts would follow firms that are listed on Swedish stock markets. Hence, we search on DataStream for all the firms whose stock exchanges are labelled with 'Stockholm'. Then we obtain 2,892 unique security codes. After deleting 1,868 codes that do not have valid I/B/E/S firm tickers, 1,024 I/B/E/S firm tickers remained;
2) Using these 1,024 I/B/E/S firm tickers as the input, we search, within the sample period, the Recommendation file and the Target Price file in I/B/E/S, for the record of analysts that appear in these files, in an attempt to obtain their

[31] Nelson Investment Research Directory used to provide analysts' biographical information, such as their names, brokerage houses, address etc. But it has stopped being updated since 2008.

analyst codes, surnames, initials of their first names and the abbreviations of their brokerage houses. Then we obtain 1,879 unique analysts' codes. The I/B/E/S firm tickers reduce from 1,024 to 565;

3) Then we manually match analysts' biographical information and their coverage lists from I/B/E/S with Bloomberg that provides analysts' full names and coverage portfolio. More importantly, Bloomberg also provides analysts' locations, which enables us to create the treatment group;
4) At last, we verify analysts' locations obtained from Bloomberg by searching analysts' full names and their brokerage houses on LinkedIn. In some cases, the location on Bloomberg is not the same as that on LinkedIn due to the delay in information updating (if the analyst relocates internationally).[32] Then we search the analyst's name and her brokerage house online to find her latest news, and make a judgment of which location is more likely to be the right one.

We have identified 1,582 distinct analysts with their locations successfully. The I/B/E/S firm tickers reduce from 565 to 554. Table 1.1 Panel (B) reports analysts' geographical distribution.[33] The majority of analysts are from the UK (658 UK analysts), followed by 223 Swedish analysts, 209 analysts from Norway and 151 US analysts. Swedish analysts are the major party influenced by the RPA adoption in Sweden so that we use 219 Swedish analysts as the treatment group and 1,359 non-Swedish analysts as the control group (Panel (C)).[34] Panel (D) reports how analysts from different countries cover these 554 Stockholm listed firms. Swedish analysts cover the most Stockholm listed firms (nearly 80%). Although the number of UK analysts is the largest, they cover less than 30% of these Stockholm listed firms. This suggests that the UK analyst coverage concentrates on a small group of Stockholm listed firms. Norwegian analysts are similar to UK analysts. 209 Norwegian analysts are identified but they cover only one third of Stockholm listed firms. Turning to analysts from other countries, they only cover a tiny portion of Stockholm listed firms.

[32] It could be that analysts have yet updated their LinkedIn profiles, or Bloomberg has yet captured analysts' latest forecasts information from their new employers.

[33] Twenty-one analysts relocated internationally during the sample period. So the total number of analysts with the identified location reported in Table 1.1 Panel (B) is 1,603. After subtracting the replicated 21 analysts, we have 1,582 distinct analysts.

[34] We deleted four analysts that relocated between Sweden and the other countries during the sample period.

1.4.2 Other data collection.

We collect analysts-related data from I/B/E/S, and accounting fundamentals from Bloomberg. Firstly, for the Hypothesis 1, the dependent variable is the number of firms followed by each analyst within a quarter (*NUMCOM*). We construct this variable by counting the number of distinct firms to whom analyst *j* had provided any forms of analysts' opinion in quarter *t*. Analysts' opinion includes recommendations, target price and all types of forecasts (earning per share, cash flow per share, short-term, long term etc). Turning to Hypothesis 2, we switch the unit of analysis from the analyst-quarter basis to the firm-quarter basis. We measure the dependent variable, Swedish analyst following (*SW_AF*), by counting the number of distinct Swedish analysts that issue recommendations, target price or all forms of forecasts for firm *i* in quarter *t*. The extant literature normally uses the issuance of the one-year-ahead EPS forecast to be the proxy of analyst following (Piotroski and Roulstone 2004; Kirk 2011). In this paper, as we conduct the tests on a quarterly basis, some analysts may not provide one-year-ahead EPS forecasts in every quarter. In order to reduce the miscounting of *NUMCOM* and *SW_AF*, we include all forms of forecasts, together with recommendations and target price. With regard to the accounting fundamental variables for Hypotheses 2 to 4, we obtain the market value of equity, the market-to-book ratio, intangible assets, total assets, the stock price, and institutional ownership from Bloomberg.[35] All variables are on a quarterly basis.

1.4.3 General description of Swedish asset management industry and Swedish stock markets.

Swedish asset management companies invest globally. The SIFA report – "Outlook about funds 2015" demonstrates the geographical description of Swedish funds' investment. The net assets in the entire asset management industry under the heading of "Sweden" and "Sweden and Global" amounts to 40% invested in equity investment.[36] There are five stock markets in Sweden, including two regulated markets – Nasdaq OMX Stockholm and Nordic Growth Market; and three multilateral trading facilities – First North Stockholm, Nordic MTF and Aktietorget. Nasdaq OMX Stockholm is the largest exchange, where the listed firms have the greatest analyst

[35] We use Bloomberg to download accounting fundamentals as Bloomberg can convert different currencies to Swedish Krona when downloading them, which reduces the currency error for firms from different countries that are listed or cross-listed in Sweden.
[36] Swedish Investment Fund Association (2015): Outlook About Funds, Page 18.

following and have an aggregated market value of equity accounting for 99% among the five markets at the end of 2013.[37] Firms listed on the remaining four markets are barely followed by any analyst. In an attempt to ensure the homogeneity of the market and increase the test power for Hypotheses 2 and 5, we focus on the firms that are listed on the Nasdaq OMX Stockholm only.[38]

1.5 Empirical results

1.5.1 Results for analysts' coverage list reduction

This section presents the results for Hypothesis 1, which is that the RPA adoption reduces analysts' coverage lists. Table 1.2, Panel (A) reports the descriptive statistics. Swedish analysts on average follow fewer firms and more industries, compared to the non-Swedish analysts. The major difference between Swedish and non-Swedish analysts is the dependent variable – the number of firms followed by an analyst. On average, Swedish analysts follow 8.11 firms whilst non-Swedish analysts cover around 2.76 more firms than Swedish analysts. Panel (C) of Table 1.2 reports the results of the regressions with different specifications. The coefficient for the interaction term $RPA \times SW$ captures the difference of the change between Swedish analysts and non-Swedish analysts in terms of the number of firms in their coverage list after RPA is adopted in Sweden. All models report negatively significant coefficients, ranging from -1.009 to -0.561.[39] In particular, in column (vi), where we include analyst and quarter fixed effects, the estimated coefficient on the interaction term is -0.623, meaning Swedish analysts on average drop 0.623 more firms relative to non-Swedish analysts after RPA is adopted. With respect to other control variables, the number of industries *NUMIND* is positively significant, indicating that analysts following more industries cover more companies. Next, we have positively significant coefficients on analysts' general experience (*GEXP*), which is in line with our assumption that analysts with more experience tend to cover more firms. Lastly, the score for analysts' accuracy in the previous year (*PACY*) has positive coefficients after we introduce fix effect structures, consistent with the expectation that analysts with

[37] The Riksbank – The Swedish Financial Market Report (2014), page 55-56.

[38] We use Nasdaq OMX Stockholm All-Share index to identify firms listed on Nasdaq OMX Stockholm. Nasdaq OMX Stockholm All-share index consists of all the shares listed on the OMX Stockholm exchange. We identify the quarterly index composite from Bloomberg.

[39] To avoid the issue of perfect multicollinearity, we drop RPA_t when the model includes quarter fixed effect, and SW_j when the model includes analyst or brokerage house fixed effects.

higher past accuracy are more likely to cover more firms. Overall, the results support Hypothesis 1. The RPA model adopted by Swedish asset managers reduces in analysts' research income. Accordingly, Swedish analysts, as the heavily influenced party, reduce the number of firms on their coverage lists.

1.5.2 Results for selective reduction in analyst following

In this section, we report the results for Hypotheses 2a, 2b, and 2c, which is that the reduction in analyst following is greater for firms with lower institutional investor holdings, small firms, or firms that are not the Benchmark index composite. We focus on Swedish analysts only and firms listed on the Nasdaq OMX Stockholm. During the sample period, 324 firms are listed on Nasdaq OMX Stockholm. Most of them are in the sectors of Consumer, Industrials, and Financials. Firms with headquarters in Sweden amount to 293. The remaining 31 firms are from other countries.[40]

Panel (A) of Table 1.4 reports the statistic description. Swedish analyst following is positively skewed and more than 25% firms have no Swedish analysts followed. Panel (C) presents the results for testing the impact of the RPA adoption on the low institutional holding firms, while Panels (D) are for the firms with low market value of equity. In addition, Panel (E) are for firms that are not included in the Benchmark index. The results are consistent with our expectation. In column (ii) of Panel (C) where we control for firm fixed effect, the coefficient of RPA is insignificant, which indicates that firms with high institutional holdings are not affected by the RPA adoption. In addition, the interaction term $RPA \times LOWINST$ is negatively significant at 10% level, suggesting that firms with low institutional investor ownership experience a greater reduction in Swedish analyst following with the RPA adoption in Sweden. The overall effect of the RPA adoption on the low institutional holding firms is 0.240, and significant at 1% level. The result does not change even when we control for both firm and quarter fixed effects in column (iii). The coefficient on the interaction term is 0.215, which amounts to 13% of the mean of the Swedish analyst following for firms with low institutional investor holdings.[41]

[40] For simplicity, we use "Swedish firms" to represent "324 firms listed on the Nasdaq OMX Stockholm" in the following sections.
[41] The mean of Swedish analysts following the low institutional holding firms is 1.72 (untabulated). The coefficient on the interaction term is -0.215, which is 13% of the mean (0.215/1.72=13%)

Turning to the test for firms with low market value of equity (small firms) in Panel (D), the negatively significant coefficient on $RPA \times SMALL$ suggests that the reduction in Swedish analyst following is greater among small firms with the RPA adoption in Sweden. Specifically, in column (vi) where we control for firm fixed effect, we have a coefficient of -0.652 on the interaction term, meaning that small firms lose 0.652 more Swedish analysts compared to large firms after RPA was adopted, which is 72% of the mean of Swedish analysts following small firms.[42] Moreover, we conduct the test for the total decrease in Swedish analyst following among small firms ($RPA + RPA \times SMALL$) and the result in column (vi) suggests that small firms lose 0.424 Swedish analysts after Swedish asset managers adopt the RPA model. The mean of Swedish analyst following for small firms before the RPA adoption is 1.11 (untabulated). The RPA adoption is associated with small firms losing more than one third of Swedish analyst following.

Finally, we present the test results with firms' index partition in Panel (E), the results are similar to the size partition in Panel (D). We find a negatively significant coefficient on $RPA \times NOBENCH$, which indicates that firms not included in the Nasdaq OMX Stockholm Benchmark index lose more analyst following than the firms in the index.

Next, we did a placebo test for the selective reduction in an attempt to mitigate the potential endogeneity concern as we lack a valid control group. We create an indicator variable *PRE*, which takes a value of one if the observation is from 2013 onward, and zero otherwise, and we run the regression (1.5). The last columns in Panel (C), Panel (D), and Panel (E) report the results. Consistent with our expectation, we only find the significant coefficients on the interaction term with *RPA*, not *PRE*, indicating that the selective reduction in analyst following is associated with the RPA adoption, rather than one year prior to the adoption. In sum, we find the evidence that the RPA adoption is associated with greater reduction in analyst following among firms with lower institutional investor ownership or lower market value of equity, as well as firms that are not included in the Benchmark index.

[42] The mean of Swedish analysts following small firms is 0.91 (untabulated). The coefficient on the interaction term is -0.652, which is 72% of the mean (0.652/0.91=72%)

1.5.3 Results for analysts' research quality

This section presents the results for the tests of analysts' research quality. We firstly use analysts' entire firm coverage to run the regression, which includes firms covered by Swedish analysts only (the A area in Figure 1.3), firms covered by non-Swedish analysts only (the B area in Figure 1.3), and firms covered by both Swedish analysts and non-Swedish analysts (the C area in Figure 1.3). As we argued in Section 2.4 that the heterogeneity of firms' location in the treatment and control group may pose a threat to the parallel trend assumption, we further conduct our test with the firms that are covered by both Swedish analysts and non-Swedish analysts within the same year (the C area only in Figure 1.3). We present both results. Panel (A) of Table 1.5 shows the descriptive statistics of the variables used in the regression. The average forecast error for Swedish analysts is 1.63%, compared to 1.92% for non-Swedish analysts. In addition, firms covered by Swedish analysts are generally smaller, have lower analyst following, more intangible assets, higher market-to-book ratio, and less negative EPS than firms followed by non-Swedish analysts. Panel (C) of Table 1.5 reports the results of regressions with different specifications within the sample contains the entire firm coverage (the A, B, and C area in Figure 1.3). With the attrition of the data process, we have 3,590 firms, 161 Swedish analysts, and 1,212 non-Swedish analysts in the regression. The coefficient on the interactive term captures the result in the difference-in-difference setting. We obtain negatively significant coefficients on $RPA \times SW$ across all specifications, suggesting that Swedish analysts experienced a decrease in forecast error, relative to non-Swedish analysts after the RPA adoption in Sweden.[43] More precisely, in column (iii), where we control for analyst, firm and quarter fixed effects, the coefficient on the interaction term is -0.327, indicating that the forecast error of Swedish analysts decreased by 0.327% more than non-Swedish analysts in the post period of the RPA adoption in Sweden. The average forecast error of Swedish analysts in the pre-adoption period is 1.98% (untabulated). The reduction in Swedish analysts' forecast error amounts to 16.5% of the mean of forecast error, compared to non-Swedish analysts.[44] Panel (D) in Table 1.5 reports the results within the sample that only contains firms covered by both Swedish analysts and non-Swedish analysts. We find 223 out of 3,590 firms covered both analysts within the same year. The sample

[43] Similar to models for Hypothesis 1, we exclude *RPA* when the model has quarter fixed effect, and drop *SW* when the model includes analyst fixed effect.

[44] The mean is 1.98%, then 0.327% / 1.98% = 16.5%.

size shrinks significantly. The observations drop from 167,468 to 36,505. The results are qualitatively unchanged, compared to that in Panel (C). After controlling for firm, analyst, and quarter fixed effects, we find that the coefficient on the interaction term is -0.262, and significant at 5% level.

Turning to the channels through which the improvement in analysts' forecast accuracy is achieved, we posit two possible channels: (1) analysts improve their forecast ability per se (Hypothesis 4a); and (2) analysts stop issuing forecasts for firms that they are unable to provide high-quality forecasts on (Hypothesis 4b). Column (iv) of Panel (C) and Panel (D) in Table 1.5 reports the results of testing the first possible channel. We restrict the sample to analyst-firm pairs appearing in both pre- and post-RPA period, and run the regression with the analyst-firm fixed effect. The results are very similar to the full sample. Specifically, in Panel (C) forecast error for Swedish analysts decreases by 0.379% relative to non-Swedish analysts after the RPA is adopted in Sweden. Thus the result is consistent with the Hypothesis 4a where the improvement in forecast accuracy is attributable to the improvement in analysts' forecast ability. With respect to the second possible channel that Swedish analysts are more likely to drop the firms if they are unable to provide high quality forecasts, we do not find any evidence to support this hypothesis. Table 1.6 reports the results. The coefficient on the interaction term is not significant at any conventional level, indicating that the likelihood of dropping coverage between Swedish analysts and non-Swedish analysts is not significantly different.

1.5.4 Results for the market reaction to analysts' forecast revisions

This section reports the results for the test of the market reaction to analysts' forecast revisions. Table 1.7, Pane (B) presents the overall results in different specifications, which are consistent with our hypotheses. Specifically, in column (ii) where we control for firm times quarter fixed effect and day fixed effect, the estimated coefficient on *ANALYST* is 0.15 and significant at 1% level. This suggests that the daily market reaction to analysts' forecast revisions is on average 0.15% higher than that without forecast revisions before the RPA adoption. In addition, we obtain a positively significant coefficient of 0.06 on *ANALYST* × *RPA*, indicating that the market reaction to forecast revisions increases by 40% in the post RPA period, relative to that in the pre-RPA period. Turning to the earnings announcement dummy (*EARN*), the estimated coefficient is 1.44 and significant at 1% level. This compares to the mean of the daily absolute abnormal return, 1.43%, as reported in Panel (A). When firms announce their earnings, the size-adjusted absolute abnormal return almost doubles. However, we do not find any change in the market reaction to earnings announcements with the RPA adoption, as the interaction term, *EARN* × *RPA*, is not significant at any conventional level. Columns (iii) and (iv) of Table 1.7 report the placebo tests. We continue finding significant coefficients on the interaction term of *ANALYST* with *RPA*, but fail to find that with *PRE*, indicating that the increase in the market reaction to analysts' forecast is associated with the RPA adoption, rather than one year prior to the adoption.

1.6 Conclusion

This paper examines how sell-side analysts respond to the change in asset managers' research payment method. Several of Sweden's largest asset managers separate research payments from dealing commissions by using the RPA model, leading to an overall reduction in analysts' research income. We firstly find that Swedish analysts reduce their coverage lists with the introduction of the separation, compared to non-Swedish analysts. Moreover, we find that the reduction in analyst coverage is greater for firms with lower institutional investor ownership and with lower market value of equity, as well as firms that are not included in the Nasdaq OMX Stockholm Benchmark index. Secondly, we find that the overall research quality has improved in the post period of the RPA adoption, and the improvement is attributable to the improvement in analysts' forecast ability, rather than the elimination of supply of forecast by lower quality analysts. Lastly, we use the size-adjusted absolute abnormal return as the proxy of market reaction, and find an increase in market reaction to forecast revisions with the RPA adoption.

A number of caveats apply to this paper. First, the setting was born with noise. Swedish analysts are not perfect to serve as the treatment group because they may provide research services to asset managers who continue using the bundled model. In a similar vein, non-Swedish analysts as the control group may be influenced by the RPA adoption in Sweden if those largest Swedish asset managers are also their important clients. Second, the way that we collect data may bring noise. Ideally, to create a control group, we need to identify analysts that do not provide any service to Swedish asset managers. Our control group have non-Swedish analysts that have history covering Swedish firms, so that they may serve Swedish asset managers as well. Therefore, the result we obtained is biased towards no result. Third, the causality for testing the selective reduction and the increase in market reaction to forecast revisions is a concern, as the test does not have the treatment/control structure. Although we did placebo tests, we cannot completely address this issue. Fourth, sell-side analyst research services are more than just issuing forecasts. Other services such as corporate access and broker-hosted conferences are also valuable to asset managers (Brown et al. 2015). Due to the data limitation, we are unable to measure them easily at this stage, which is a fruitful research area in future if data are available.

1.7 Appendix: Definition of variables

Firm-level variables		
Variable Name	Description	Source
ABS_ABRET	The size-adjusted absolute abnormal return in the percentage form, calculated by taking the absolute value of the difference between firms' daily return and the daily OMX Stockholm large-cap, medium-cap, or small-cap index returns, depending on the firms' inclusion of each index.	Bloomberg
AF_SW	The number of Swedish analysts issuing any form of forecasts (EPS, CPS, one-year-ahead, two-year-ahead etc), recommendations, or target price to a firm within a quarter.	I/B/E/S
ANALYST	Dummy variable, with the value of one if any analyst provides forecast revisions on the day and the next day ([0, +1]), and zero otherwise.	I/B/E/S
DECL	Dummy variable, set equal to one if the firm's EPS is lower than that in the previous year, and zero otherwise.	I/B/E/S
EARN	Dummy variable, with the value of one if a firm makes an earnings announcement on the day and the next day ([0, +1]), and zero otherwise.	I/B/E/S
INST	The percentage of institutional investor ownership.	Bloomberg
INTA	Intangible assets scaled by total assets.	Bloomberg
LOSS	Dummy variable, set equal to one when actual EPS is negative, and zero otherwise.	I/B/E/S
LOWINST	Dummy variable, set equal to one when the firm has the institutional ownership lower than the median of all firms at the end of the last quarter in 2014, and zero otherwise.	Bloomberg
MB	Market value of equity divided by book value of equity.	Bloomberg
MV	The market value of equity in the logarithm form.	Bloomberg
NOBENCH	Dummy variable, set equal to one if the firm is included in the Nasdaq OMX Stockholm Benchmark index at the end of the last quarter in 2014, and zero otherwise.	Bloomberg
RETVOL	Standard deviation of daily stock returns within each quarter.	Bloomberg
RPA	Dummy variable. It equals to one when the observation is from the period after RPA is adopted in Sweden, and zero otherwise.	
PRE	Dummy variable. It equals to one when the observation is from 2014 onwards, and zero otherwise.	
RSQ	R-squared from a regression of daily stock return on the market return within each quarter.	Bloomberg

SMALL	Dummy variable, set equal to one when the firm is defined as a small firm, and zero otherwise. Small firms are defined as the market value of equity of the firm is less than median of all firms at the end of the last quarter in 2014.	

Analyst-level variables		
Variable Name	Description	Source
BROSIZE	The number of analysts employed within a brokerage house within a quarter.	I/B/E/S
DIS	Dummy variable, set value of one if the analyst-firm pairs disappeared in the post RPA adoption period, and zero otherwise.	I/B/E/S
FEXP	Firm-specific experience in the logarithm form. Firm-specific experience is measured as the number of years from the analyst's first opinion on the specific firm to present.	I/B/E/S
FORERR	Analyst forecast error, defined as the absolute value of the difference between the one-year ahead EPS forecast and the actual EPS, scaled by the stock price two days before the issuance of the forecast, then times 100.	I/B/E/S
GEXP	General experience in the logarithm form. Analysts' general experience is measured as the number of years from the analyst's first opinion on any firm to present.	I/B/E/S
HOR	Forecast horizon in the logarithm form. Forecast horizon is the number of days between the date when the forecast is issued and the date when the actual EPS is announced.	I/B/E/S
NUMCOM	Total number of firms covered by an analyst.	I/B/E/S
NUMIND	Total number of industries (two-digit SIC codes) covered by an analyst.	I/B/E/S
PACY	Analyst relative accuracy score in the previous year, which is calculated in line with the method in Hong and Kubik (2003).	I/B/E/S
SW	Dummy variable, set equal to one when the forecast is issued by an analyst who locates in Sweden, and zero otherwise.	I/B/E/S, *LinkedIn*

1.8 Appendix: The full Article 17 in the Commission Delegated Directive (EU) 2017/593

The Research Payment Account related rules in MiFID II below is taken from the Commission Delegated Directive (EU) 2017/593. Online available: http://data.europa.eu/eli/dir_del/2017/593/oj

L 87/516 EN Official Journal of the European Union 31.3.2017

Article 13

Inducements in relation to research

1. Member States shall ensure that the provision of research by third parties to investment firms providing portfolio management or other investment or ancillary services to clients shall not be regarded as an inducement if it is received in return for either of the following:

(a) direct payments by the investment firm out of its own resources;

(b) payments from a separate research payment account controlled by the investment firm, provided the following conditions relating to the operation of the account are met:

(i) the research payment account is funded by a specific research charge to the client;

(ii) as part of establishing a research payment account and agreeing the research charge with their clients, investment firms set and regularly assess a research budget as an internal administrative measure;

(iii) the investment firm is held responsible for the research payment account;

(iv) the investment firm regularly assesses the quality of the research purchased based on robust quality criteria and its ability to contribute to better investment decisions.

With regard to point (b) of the first subparagraph, where an investment firm makes use of the research payment account, it shall provide the following information to clients:

(a) before the provision of an investment service to clients, information about the budgeted amount for research and the amount of the estimated research charge for each of them;

(b) annual information on the total costs that each of them has incurred for third party research.

2. Where an investment firm operates a research payment account, Member States shall ensure that the investment firm shall also be required, upon request by their clients or by competent authorities, to provide a summary of the providers paid from this account, the total amount they were paid over a defined period, the benefits and services received by the investment firm, and how the total amount spent from the account compares to the budget set by the firm for that period, noting any rebate or carry-over if residual funds remain in the account. For the purposes of point (b)(i) of paragraph 1, the specific research charge shall:

(a) only be based on a research budget set by the investment firm for the purpose of establishing the need for third party research in respect of investment services rendered to its clients; and

(b) not be linked to the volume and/or value of transactions executed on behalf of the clients.

3. Every operational arrangement for the collection of the client research charge, where it is not collected separately but alongside a transaction commission, shall indicate a separately identifiable research charge and shall fully comply with the conditions set out in point (b) of the first subparagraph of paragraph 1 and in the second subparagraph of paragraph 1.

4. The total amount of research charges received may not exceed the research budget.

5. The investment firm shall agree with clients, in the firm's investment management agreement or general terms of business, the research charge as budgeted by the firm and the frequency with which the specific research charge will be deducted from the resources of the client over the year. Increases in the research budget shall only take place after the provision of clear information to clients about such intended increases. If there is a surplus in the research payment account at the end of a period, the firm should have a process to rebate those funds to the client or to offset it against the research budget and charge calculated for the following period.

6. For the purposes of point (b)(ii) of the first subparagraph of paragraph 1, the research budget shall be managed solely by the investment firm and shall be based on a reasonable assessment of the need for third party research. The allocation of the research budget to purchase third party research shall be subject to appropriate controls and senior management oversight to ensure it is managed and used in the best interests of the firm's clients. Those controls include a clear audit trail of payments made to research providers and how the amounts paid were determined with reference to the quality criteria referred to in paragraph 1 (b) (iv). Investment firms shall not use the research budget and research payment account to fund internal research.

7. For the purposes of point (b)(iii) of paragraph 1, the investment firm may delegate the administration of the research payment ac-count to a third party, provided that the arrangement facilitates the purchase of third party research and payments to research providers in the name of the investment firm without any undue delay in accordance with the investment firm's instruction.

8. For the purposes of point (b) (iv) of paragraph 1, investment firms shall establish all necessary elements in a written policy and provide it to their clients. It shall also address the extent to which research purchased through the research payment account may benefit clients' portfolios, including, where relevant, by taking into account investment strategies applicable to various types of portfolios, and the approach the firm will take to allocate such costs fairly to the various clients' portfolios.

9. An investment firm providing execution services shall identify separate charges for these services that only reflect the cost of executing the transaction. The provision of each other benefit or service by the same investment firm to investment firms, established in the Union shall be subject to a separately identifiable charge; the supply of and charges for those benefits or services shall not be influenced or conditioned by levels of payment for execution services.

1.9 Appendix: Swedish Code of Conduct for fund management companies

This graph presents the codes relating to the research payment separation in Sweden, taken from the page 6 in Swedish Code of Conduct for fund management companies issued on 26 March 2015. Online available at: http://fondbolagen.se/en/Regulations/Guidelines/Code-of-conduct/

Fondbolagens förening
SWEDISH INVESTMENT FUND ASSOCIATION

External distribution
The fund management company should, by means of written agreements with distributors, work to ensure that the distributor undertakes to comply with the Swedish Investment Fund Association's Guidelines for marketing and information by fund management companies, in connection with his or her brokering of the fund management company's funds.

The fund management company must provide the distributor with the necessary product information and support with regard to the fund management company's fund products so that best practices regarding financial advice can be maintained.

Brokers and other trading partners
The fund management company must have a documented process for choosing brokers and other trading partners. When choosing partners for the execution of orders, the partner's ability to provide investment research must not be taken into account.

Costs for investment research may be charged with the fund only where the research enhances the quality of the fund management and the unit-holders have been duly informed. This requires that the benefit of the research is considered to correspond to the costs. The costs for research must be separated from the costs for execution of orders.

The above mentioned must be monitored by the Board of Directors or the CEO.

1.10 Appendix: An excerpt from the Information Brochure of Handelsbanken Fund AB

This graph presents the announcement from one of the Swedish asset management companies, Handelsbanken, separating the research payment (expenses for external analyses) from the dealing commissions in the Information Brochure (page 8).

Online available https://www.medirect.be/getdocument.aspx?id=103670455

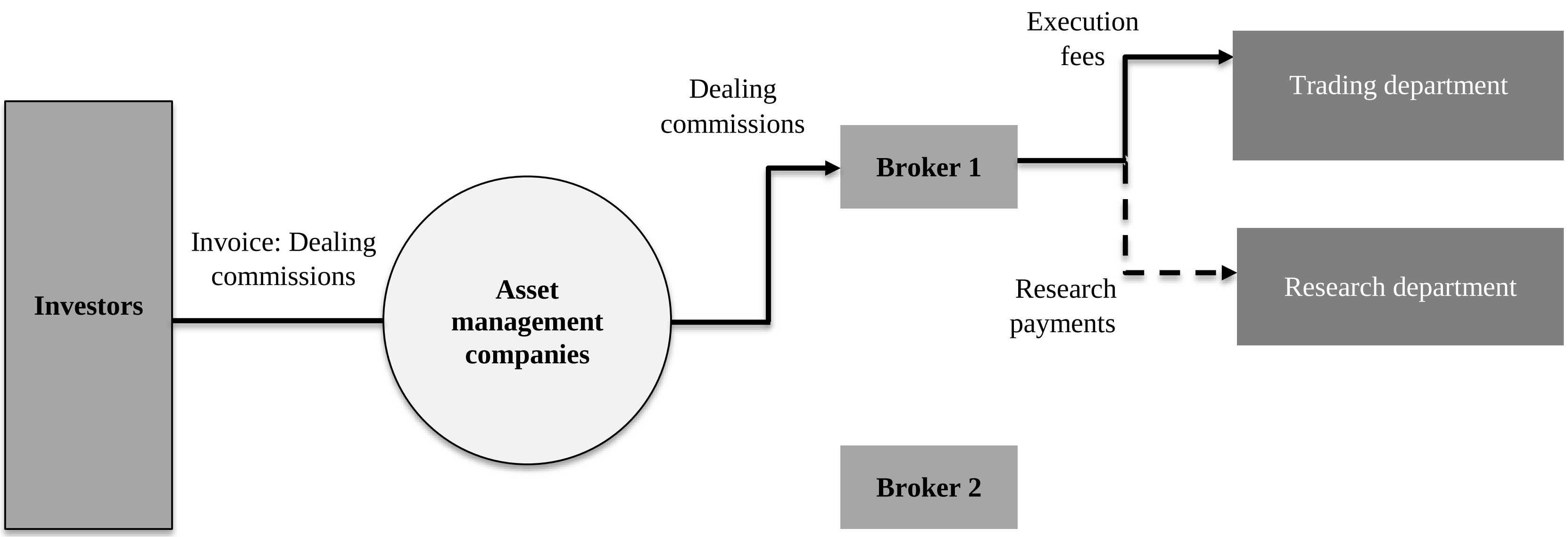
Information Brochure -
Handelsbanken Fonder AB

January 12, 2016

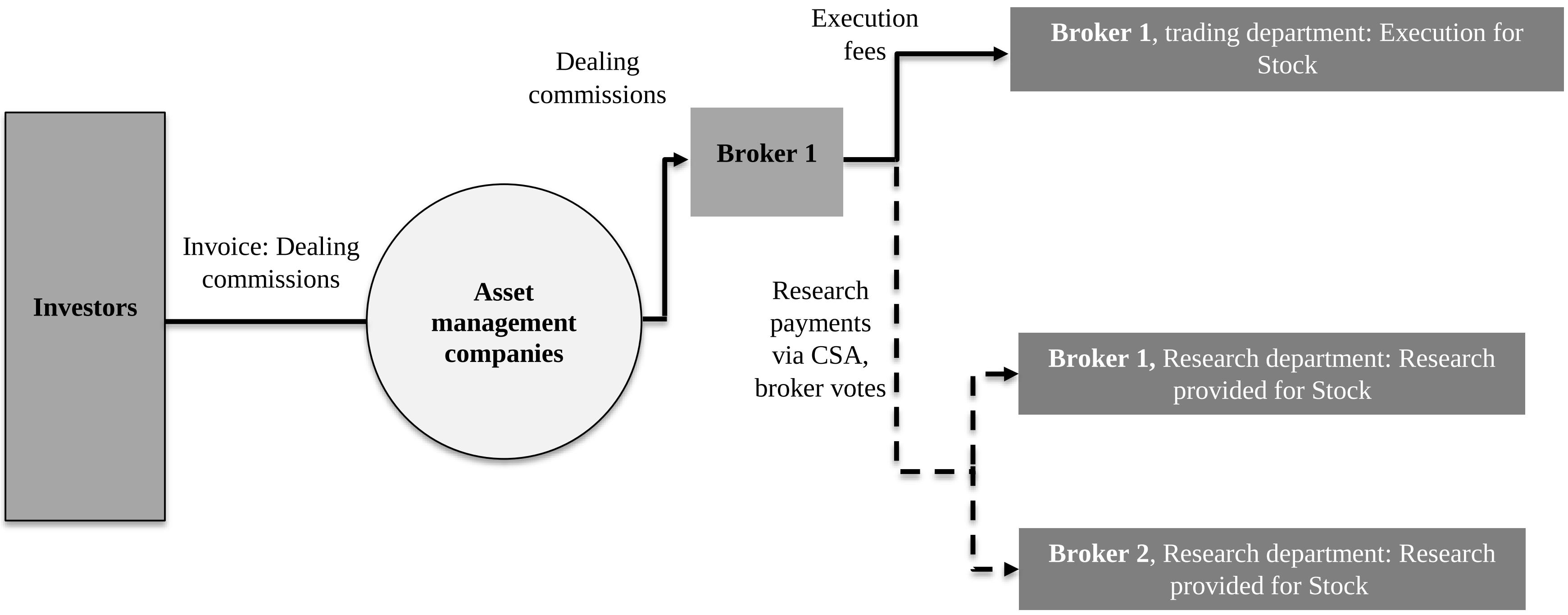
In practice, costs are deducted from each fund in the same manner as the management fee. However, the research firms invoice the Management Company on a quarterly basis, while the funds benefit daily from the purchase of the analyses. As of January 1, 2015, expenses for external analyses will be charged separately. These expenses were previously included in the transaction costs. The expenses for external analyses will be included in the calculation of the annual fee.

Figure 1.1: The Bundled Model, Research Payment Account (RPA), and Commission Sharing Agreement (CSA)

Panel (A): The Bundled Model



Panel (B): The Modified Bundled Model – Commission Sharing Agreement (CSA)



Panel (C): Research Payment Accounting (RPA)

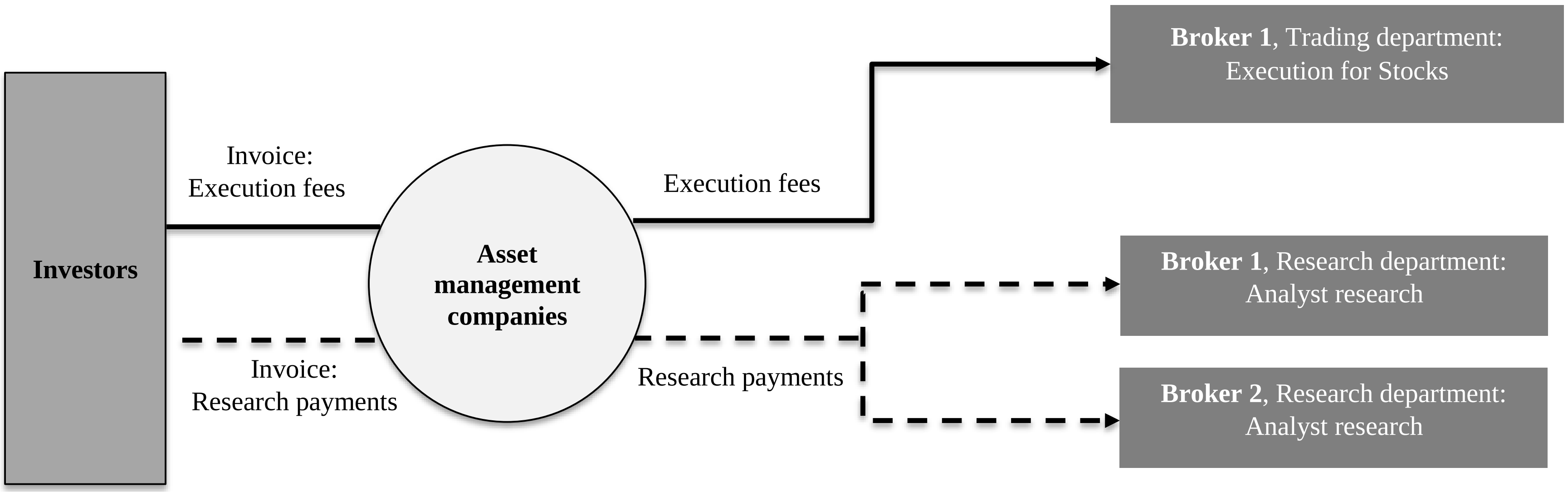


Figure 1.2: The identification of the treatment group and the control group

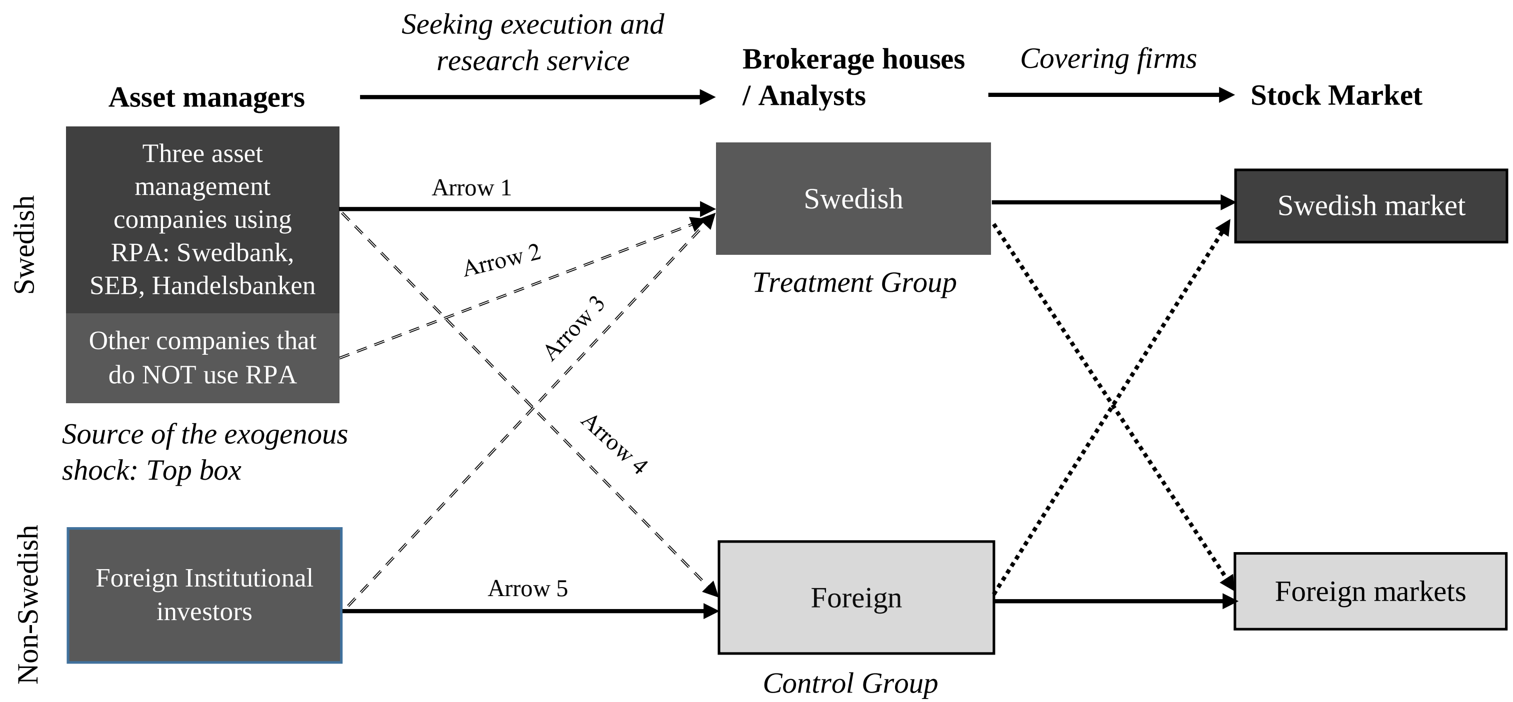


Figure 1.3: Firm coverage of analysts in treatment group and control group

This graph shows the firms covered by analysts in the treatment group and/or in the control group. The oval with solid line represents firm covered by Swedish analysts (treatment group). The oval with dotted line represents firm covered by non-Swedish analysts (control group). The A area are firms covered by Swedish analysts but not by non-Swedish analysts. The B area are firms covered by non-Swedish analysts but not by Swedish analysts. The C area are firms covered by both Swedish analysts and non-Swedish analysts.

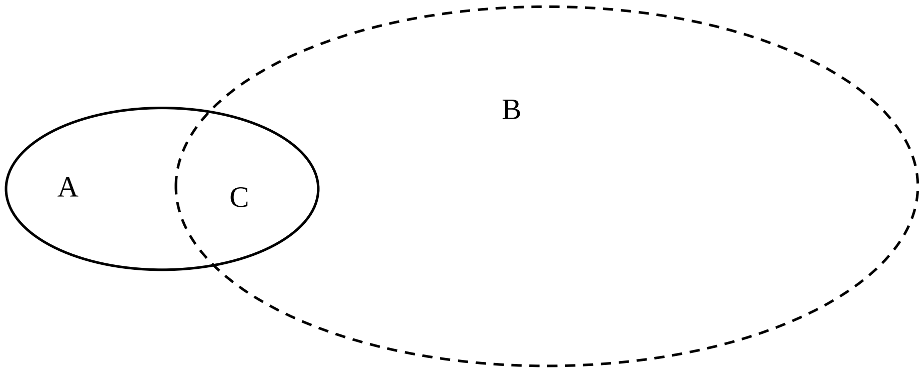


Table 1.1: The identification of analysts' location

This table reports the process of identifying analysts' location, the geographical distribution of identified analysts, and the number of firms covered by analysts from each country. The data is hand collected from I/B/E/S, Bloomberg and LinkedIn. Panel (A) reports the process of identifying analysts' location. Panel (B) shows the locations of all analysts identified. Panel (C) presents the analysts that are chosen in the treatment group and the control group. Panel (D) reports the number and the percentage of Stockholm listed firms covered by analysts from different countries.

Panel (A): The process of identifying analysts' location

From DataStream	Number	Number	Number
Securities/Firms labelled as "Stockholm listed"		2,892	
Less firms that do not have a valid I/B/E/S tickers	*1,868*		
Securities/Firms with I/B/E/S tickers		1,024	
Merge these 1,024 tickers with all I/B/E/S files within 2013 to 2016			
Firms remained (tickers not found in I/B/E/S are deleted)		565	
Number of analysts covering these 565 firms		1,879	
Manually identifying the location of these 1,879 analysts			
Number of analysts identified		1,582	
Number of firms covered by identified analysts			*554*
Number of I/B/E/S error codes (one code with multiple names)		264	
Number of analysts unidentified		33	

Panel (B): Geographical distribution of identified analysts

Location	Number of analysts	Percent
UK	658	41.0%
Sweden	223	13.9%
Norway	209	13.0%
US	151	9.4%
France	69	4.3%
Canada	68	4.2%
Germany	42	2.6%
Finland	39	2.4%
Denmark	22	1.4%
Netherlands	20	1.2%
Russia	19	1.2%
Switzerland	18	1.1%
Lithuania	11	0.7%
South Africa	8	0.5%
Italy	7	0.4%
Poland	6	0.4%
India	5	0.3%
Australia	4	0.2%
Spain	4	0.2%
Austria	2	0.1%
Czech Republic	2	0.1%
HK	2	0.1%
Korea	2	0.1%
Portugal	2	0.1%
Tunisia	2	0.1%
Brazil	1	0.1%
Ireland	1	0.1%
Malaysia	1	0.1%
Mexico	1	0.1%
New Zealand	1	0.1%
Singapore	1	0.1%
Turkey	1	0.1%
United Arab Emirates	1	0.1%
Total	1,603	100%
less analysts relocated internationally	*21*	
Distinct analysts identified	1,582	

Panel (C): Treatment group and control group

Treatment Group	
No. of analysts in Sweden	223
Less no. of analysts used to relocate between Sweden and other countries	*4*
No. of analysts in the treatment group	**219**

Control Group	
No. of non-Swedish analysts in the control group	**1,359**

Panel (D): Number of Stockholm listed firms covered by analysts from each country

Total number of Stockholm listed firms covered by identified analysts	**554**	(denominator)

Firms covered by analysts from …	Number of firms	Percent
Sweden	431	77.8%
Norway	197	35.6%
UK	164	29.6%
US	68	12.3%
France	64	11.6%
Finland	56	10.1%
Denmark	42	7.6%
Lithuania	32	5.8%
Netherlands	31	5.6%
Germany	23	4.2%
Canada	21	3.8%
Russia	18	3.2%
India	9	1.6%
Italy	8	1.4%
Spain	8	1.4%
Switzerland	5	0.9%
South Africa	5	0.9%
Tunisia	4	0.7%
Australia	3	0.5%
Czech Republic	3	0.5%
Poland	2	0.4%
Austria	2	0.4%
Korea	2	0.4%
Portugal	2	0.4%
Brazil	1	0.2%
HK	1	0.2%
Ireland	1	0.2%
Malaysia	1	0.2%
Mexico	1	0.2%
New Zealand	1	0.2%
Singapore	1	0.2%
Turkey	1	0.2%
United Arab Emirates	1	0.2%

Table 1.2: The number of firms on analysts' coverage list

This table reports the descriptive statistics and results for Hypothesis 1 – the adoption of RPA reduces the number of firms in the analyst coverage list. The analysis is on the analyst-quarterly basis. The pre-adoption period is from 2013Q1 to 2014Q4, whilst the post-adoption period is from 2015Q1 to 2016Q4. The treatment (control) group has 219 Swedish (1,359 non-Swedish) analysts during the sample period. In this table, the dependent variable is *NUMCOM*, which is defined as the number of firms followed by each individual analyst within a quarter. *SW* is the indicator variable for the treatment group, equals to one for Swedish analysts, and zero for non-Swedish analysts. *RPA* is the indicator variable, equals to one when the observation is from post-RPA period (1 January 2015 onwards), and zero otherwise. *GEXP* is analysts' general experience in the natural logarithm form. General experience is measured as the number of years from when the analyst issued her first analyst's opinion for any firms to present. *NUMIND* denotes the number of two-digit SIC industries followed by each individual analyst. *PACY* denotes the relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). Panel (A) presents descriptive statistics for variables used in the regression. Panel (B) reports Pearson (below diagonal) and Spearman (above diagonal) correlations. The correlations significant at the 5 percent level are shown in bold. Panel (C) outlines the results. All the regressions are clustered at the analyst level and the quarter level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

Treatment: SW=1								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
NUMCOM	1,733	8.11	4.47	1	5	8	11	26
RPA	1,733	0.51	0.50	0	0	1	1	1
GEXP	1,733	2.29	0.86	0.22	1.56	2.51	3.07	3.42
NUMIND	1,733	3.39	2.23	1	2	3	4	10
PACY	1,733	54.47	16.01	14.64	44.29	54.38	64.62	88.08

Control: SW=0								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
NUMCOM	14,528	10.87	6.93	1	6	10	14	34
RPA	14,528	0.49	0.50	0	0	0	1	1
GEXP	14,528	2.25	0.81	0	1.66	2.3	3	3.43
NUMIND	14,528	2.81	1.89	1	1	2	4	10
PACY	14,528	53.49	13.16	14.64	45.54	53.73	61.45	88.08

Panel (B): Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	*NUMCOM*		**0.10**	**-0.12**	**0.23**	**0.41**	-0.00
(2)	*RPA*	**0.10**		0.01	**0.07**	**0.02**	**-0.06**
(3)	*SW*	**-0.12**	0.01		**0.02**	**0.08**	**0.02**
(4)	*GEXP*	**0.19**	**0.07**	**0.02**		**0.16**	-0.01
(5)	*NUMIND*	**0.42**	**0.03**	**0.09**	**0.15**		0.00
(6)	*PACY*	-0.01	**-0.07**	**0.02**	**-0.02**	0.00	

Panel (C): Results for testing the reduction in the number of firms on analysts' coverage lists

Dependent variable: *NUMCOM*						
Variables	i	ii	iii	iv	v	vi
RPA	1.183***	1.125***	1.216***		0.753**	
	(0.256)	(0.257)	(0.273)		(0.289)	
SW	-2.619***	-3.314***				
	(0.376)	(0.319)				
RPA × *SW*	-1.009***	-0.649**	-0.561**	-0.605**	-0.572*	-0.623**
	(0.333)	(0.230)	(0.251)	(0.249)	(0.280)	(0.275)
GEXP		1.267***	1.311***	1.277***	2.929***	1.702***
		(0.166)	(0.145)	(0.146)	(0.462)	(0.550)
NUMIND		1.411***	1.267***	1.262***	2.046***	2.043***
		(0.088)	(0.060)	(0.060)	(0.068)	(0.068)
PACY		-0.001	0.012**	0.012**	0.009**	0.008*
		(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
No. of Ob.	18,127	16,261	16,241	16,241	16,216	16,216
R-squared	0.027	0.228	0.544	0.549	0.791	0.794
Broker FE	No	No	Yes	Yes	No	No
Analyst FE	No	No	No	No	Yes	Yes
Quarter FE	No	No	No	Yes	No	Yes

Table 1.3: General description of Nasdaq OMX Stockholm

This table reports the distribution of firms listed on the largest stock market in Sweden: Nasdaq OMX Stockholm by countries of headquarters in Panel (A) and by industries in Panel (B). These firms are used to test the Hypotheses 2a to 2c – the selective reduction in firms' analyst following.

Panel (A): Countries of headquarters

Country	No. of firms	Percent
Sweden	293	90.43
Canada	8	2.47
Finland	6	1.85
Switzerland	4	1.23
Belgium	2	0.62
Denmark	2	0.62
UK	2	0.62
Luxembourg	2	0.62
US	2	0.62
Russia	1	0.31
Malta	1	0.31
Poland	1	0.31
Total	324	100

Panel (B): The industry distribution

Industry	No. of firms	Percent
Consumer, Non-cyclical	72	22.22
Industrial	65	20.06
Consumer, Cyclical	48	14.81
Financial	48	14.81
Communications	28	8.64
Technology	27	8.33
Basic Materials	20	6.17
Energy	9	2.78
Diversified	6	1.85
Utilities	1	0.31
Total	324	100

Table 1.4: Selective reduction in firms' analyst following

This table reports the descriptive statistics and results for Hypotheses 2a, 2b , and 2c – after the RPA adoption, the decrease in the number of analyst following is greater among the lower institutional holding firms, small firms, and firms that are not included in the Nasdaq OMX Stockholm Benchmark index. The test is conducted on 324 firms that are listed on the largest Swedish stock market – Nasdaq OMX Stockholm from 2013 to 2016. The analysis is on the firm-quarterly basis. The pre-adoption period is from 2013Q1 to 2014Q4, whilst the post-adoption period is from 2015Q1 to 2016Q4. The dependent variable is *AF_SW*, which is measured by the number of Swedish analysts following a firm listed on Nasdaq OMX Stockholm within each quarter. *RPA* is the indicator variable, equals to one when the observation is from post-RPA period (1 January 2015 onwards), and zero otherwise. *PRE* is the indicator variable, equals to one from 1 January 2014 onwards, and zero otherwise. *LOWINST* is a dummy variable, set equal to one when the firm has the institutional investor ownership lower than the median of all firms at the end of the last quarter in 2014, and zero otherwise. *SMALL* is an indicator variable, equals to one when the firm is defined as a small firm. Small firms are defined as when the firm's market value of equity is less than the median of all firms at the end of the last quarter in 2014, and zero otherwise. *NOBENCH* is a dummy variable, with a value of one if the firm is not included in the Nasdaq OMX Stockholm Benchmark index at the end of the last quarter in 2014, and zero otherwise. *MV* represents the market value of equity in the logarithm form. *INTA* indicates the percentage of intangible assets, and is calculated as on the total intangible assets, scaled by total assets. *MB* is the market-to-book ratio and measured by dividing the market value of equity by the book value of equity. *INST* denotes the percentage of institutional investor ownership for a firm within each quarter. *RETVOL* is the stock return volatility within each quarter. *RSQ* is the R-squared from the market model of the individual stock return on the market return. Panel (A) presents descriptive statistics for variables used in the regression. Panel (B) reports Pearson (below diagonal) and Spearman (above diagonal) correlations. The correlations significant at the 5 percent level are shown in bold. Panels (C) to (E) outline the results with different partitions. All the regressions are clustered at the firm level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

RPA=0								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
AF_SW	1,764	2.74	2.52	0.00	1.00	2.00	4.00	10.00
LOWINST	1,764	0.46	0.50	0.00	0.00	0.00	1.00	1.00
SMALL	1,764	0.52	0.50	0.00	0.00	1.00	1.00	1.00
NOBENCH	1,764	0.74	0.44	0.00	0.00	1.00	1.00	1.00
MV	1,764	7.81	2.04	2.65	6.23	7.63	9.30	12.85
INTA	1,764	0.23	0.22	0.00	0.01	0.17	0.38	0.80
INST	1,764	48.19	23.48	0.00	30.32	48.98	65.85	99.79
RSQ	1,764	0.13	0.16	0.00	0.02	0.07	0.19	0.74
RETVOL	1,764	0.02	0.01	0.01	0.01	0.02	0.02	0.09
MB	1,764	2.99	3.15	0.17	1.17	2.08	3.57	22.12

RPA=1								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
AF_SW	1,834	2.65	2.70	0.00	0.00	2.00	5.00	11.00
LOWINST	1,834	0.47	0.50	0.00	0.00	0.00	1.00	1.00
SMALL	1,834	0.51	0.50	0.00	0.00	1.00	1.00	1.00
NOBENCH	1,834	0.75	0.43	0.00	0.00	1.00	1.00	1.00
MV	1,834	8.13	2.02	2.26	6.67	8.03	9.72	12.85
INTA	1,834	0.24	0.23	0.00	0.01	0.19	0.41	0.80
INST	1,834	53.20	23.05	0.00	36.96	54.75	70.49	99.79
RSQ	1,834	0.19	0.20	0.00	0.03	0.11	0.30	0.74
RETVOL	1,834	0.02	0.01	0.00	0.02	0.02	0.03	0.09
MB	1,834	3.38	3.53	0.17	1.32	2.35	4.06	22.12

Panel (B): Correlation matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	*AF_SW*		**-0.04**	**-0.37**	**-0.71**	**-0.64**	**0.80**	**0.14**	**0.38**	**0.57**	**-0.44**	**0.17**
(2)	*RPA*	-0.02		0.01	-0.01	0.01	**0.08**	0.02	**0.11**	**0.16**	**0.10**	**0.07**
(3)	*LOWINST*	**-0.33**	0.02		**0.34**	**0.30**	**-0.37**	**-0.20**	**-0.68**	**-0.22**	**0.16**	**-0.14**
(4)	*SMALL*	**-0.66**	-0.01	**0.32**		**0.57**	**-0.84**	**0.01**	**-0.32**	**-0.55**	**0.47**	**-0.18**
(5)	*NOBENCH*	**-0.65**	0.01	**0.28**	**0.55**		**-0.66**	**0.08**	**-0.24**	**-0.53**	**0.37**	-0.03
(6)	*MV*	**0.74**	**0.08**	**-0.33**	**-0.80**	**-0.68**		-0.03	**0.38**	**0.65**	**-0.52**	**0.25**
(7)	*INTA*	**0.13**	**0.03**	**-0.18**	**0.04**	**0.06**	**-0.04**		**0.23**	**-0.05**	**0.07**	**0.11**
(8)	*INST*	**0.35**	**0.07**	**-0.65**	**-0.30**	**-0.22**	**0.31**	**0.22**		**0.26**	**-0.17**	**0.17**
(9)	*RSQ*	**0.58**	**0.15**	**-0.21**	**-0.53**	**-0.58**	**0.67**	**-0.08**	**0.20**		**-0.36**	**0.06**
(10)	*RETVOL*	**-0.35**	**0.04**	**0.17**	**0.38**	**0.27**	**-0.43**	0.00	**-0.22**	**-0.29**		0.00
(11)	*MB*	**0.06**	**0.07**	**-0.05**	**-0.08**	-0.02	**0.12**	**-0.09**	0.02	-0.02	**0.08**	

Panel (C): Results for low institutional ownership partition

Dependent variable: *AF_SW*				
	Low institutional ownership			
	i	ii	iii	iv
RPA	-0.430***	-0.034		
	(0.095)	(0.094)		
LOWINST	0.034			
	(0.203)			
RPA × *LOWINST*	-0.292**	-0.206*	-0.215**	-0.184*
	(0.124)	(0.110)	(0.108)	(0.100)
PRE × *LOWINST*				-0.065
				(0.113)
MV	0.865***	0.170**	0.232***	0.232***
	(0.052)	(0.085)	(0.083)	(0.083)
INTA	1.557***	-0.047	-0.128	-0.128
	(0.313)	(0.350)	(0.356)	(0.356)
INST	0.006	0.003	0.004*	0.004*
	(0.004)	(0.002)	(0.002)	(0.002)
RETVOL	3.959	-2.990	-2.390	-2.417
	(4.386)	(2.046)	(1.920)	(1.918)
RSQ	2.474***	0.236	0.693***	0.690***
	(0.471)	(0.158)	(0.195)	(0.194)
MB	-0.006	-0.015	-0.011	-0.012
	(0.025)	(0.010)	(0.011)	(0.011)
Observations	3,598	3,598	3,598	3,598
Adjusted R-squared	0.680	0.905	0.913	0.913
RPA + *PRA* × *LOWINST*	-0.722***	-0.240***		
	(0.090)	(0.073)		
Firm Fixed Effect	No	Yes	Yes	Yes
Quarter Fixed Effect	No	No	Yes	Yes

Panel (D): Results for the small size partition

Dependent variable: *AF_SW*				
	Small size			
	v	vi	vii	viii
RPA	-0.313***	0.228**		
	(0.113)	(0.093)		
SMALL	-0.598**			
	(0.271)			
RPA × *SMALL*	-0.424***	-0.652***	-0.620***	-0.551***
	(0.123)	(0.106)	(0.105)	(0.095)
PRE × *SMALL*				-0.147
				(0.116)
MV	0.715***	0.133*	0.200***	0.196***
	(0.069)	(0.076)	(0.075)	(0.075)
INTA	1.581***	0.015	-0.080	-0.073
	(0.306)	(0.317)	(0.323)	(0.325)
INST	0.006*	0.003	0.004*	0.004*
	(0.003)	(0.002)	(0.002)	(0.002)
RETVOL	4.748	-3.749**	-3.312*	-3.436*
	(3.946)	(1.895)	(1.796)	(1.795)
RSQ	2.466***	0.062	0.455**	0.441**
	(0.467)	(0.149)	(0.183)	(0.183)
MB	-0.004	-0.011	-0.008	-0.008
	(0.023)	(0.009)	(0.010)	(0.010)
Observations	3,598	3,598	3,598	3,598
Adjusted R-squared	0.690	0.908	0.916	0.916
RPA + *PRA* × *SMALL*	-0.737***	-0.424***		
	(0.071)	(0.067)		
Firm Fixed Effect	No	Yes	Yes	Yes
Quarter Fixed Effect	No	No	Yes	Yes

Panel (E): Results for the non-benchmark stock partition

Dependent variable: *AF_SW*				
	Non-bench Stocks			
	ix	x	xi	xii
RPA	-0.100	0.215*		
	(0.135)	(0.127)		
NOBENCH	-1.304***			
	(0.280)			
PRA × *NOBENCH*	-0.471***	-0.459***	-0.446***	-0.395***
	(0.147)	(0.141)	(0.139)	(0.132)
PRE × *NOBENCH*				-0.107
				(0.143)
MV	0.692***	0.169**	0.234***	0.234***
	(0.057)	(0.080)	(0.078)	(0.078)
INTA	1.671***	-0.073	-0.162	-0.165
	(0.282)	(0.343)	(0.350)	(0.350)
INST	0.007**	0.003	0.004*	0.004*
	(0.003)	(0.002)	(0.002)	(0.002)
RETVOL	1.029	-3.420*	-2.883	-2.922
	(3.800)	(1.986)	(1.865)	(1.862)
RSQ	1.560***	0.166	0.594***	0.585***
	(0.446)	(0.159)	(0.194)	(0.196)
MB	0.002	-0.015	-0.012	-0.012
	(0.022)	(0.010)	(0.011)	(0.011)
Observations	3,598	3,598	3,598	3,598
Adjusted R-squared	0.713	0.906	0.914	0.914
RPA + *PRA* × *NOBENCH*	-0.571***	-0.244***		
	(0.074)	(0.069)		
Firm Fixed Effect	No	Yes	Yes	Yes
Quarter Fixed Effect	No	No	Yes	Yes

Table 1.5: Analysts' research quality

The table reports the test for analysts' research quality. Panel (A) reports descriptive statistics. In this table, *FORERR* is the dependent variable, which is defined as analyst forecast error and calculated by taking the absolute value of the difference between the one-year-ahead EPS forecast and the actual EPS, scaled by the stock price two days before the forecast is provided, then multiplied by 100. *SW* is the indicator variable for the treatment group, equals to one for Swedish analysts, and zero for non-Swedish analysts. *RPA* is the indicator variable, equals to one when the observation is from post-RPA period (1 January 2015 onwards), and zero otherwise. *MV* represents the market value of equity in the logarithm form. *AF* is the total number of analysts following a firm within each quarter. *INTA* indicates the percentage of intangible assets scaled by total assets. *MB* is the market-to-book ratio and measured by dividing the market value of equity by the book value of equity. *RETVOL* is the stock return volatility within each quarter. *LOSS* is a dummy variable, and equals to one when the actual EPS is negative, and zero otherwise. *DECL* is a dummy variable, and equals to one when the current actual EPS is less than the EPS in the previous year. *HOR* denotes the forecast horizon in the logarithm form. Forecast horizon is the number of days between the date when the forecast is provided and the date when the actual EPS is announced. *FEXP* is the analyst's experience to a specific firm in the logarithm form. Analyst's experience to a specific firm is measured as the number of years since the analyst provides her first analyst's opinion on the specific firm to present. *GEXP* is analysts' general experience of being an analyst in the logarithm form. Analysts' general experience is measured as the number of years from when the analyst issued her first analyst's opinion for any firms to present. *NUMCOV* and *NUMIND* are total numbers of firms and industries that one analyst covers within each quarter respectively. *PACY* denotes the relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). Panel (B) reports Pearson (below diagonal) and Spearman (above diagonal) correlations. The correlations significant at the five percent level are shown in bold. Panels (C) and (D) outlines the results within the full sample and the mutual coverage sample respectively. Columns (i) to (iii) report the results in the full sample. Column (iv) reports the result within the sample restricting to analyst-firm pairs appearing in the both pre- and post-adopting period. All the regressions are clustered at the analyst level and the quarter level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

Treatment: SW=1								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
FORERR	15,739	1.63	3.91	0	0.19	0.57	1.48	35.09
RPA	15,739	0.52	0.50	0	0	1	1	1
MV	15,739	7.76	1.72	3.82	6.61	7.82	8.94	12.19
AF	15,739	13.17	9.68	1	5	10	21	61
INTA	15,739	26.64	22.14	0	6.24	24.43	41.55	77.43
MB	15,739	3.25	3.70	-8.58	1.50	2.51	3.75	26.44
RETVOL	15,739	0.02	0.01	0	0.01	0.02	0.02	0.06
LOSS	15,739	0.09	0.29	0	0	0	0	1
DECL	15,739	0.39	0.49	0	0	0	1	1
HOR	15,739	5.26	0.52	3.43	4.79	5.35	5.67	5.90
FEXP	15,739	1.49	0.85	0	0.79	1.49	2.19	3.11
GEXP	15,739	2.46	0.81	0.13	1.83	2.8	3.12	3.42
NUMCOM	15,739	10.48	4.36	1	7	10	13	26
NUMIND	15,739	4.16	2.43	1	2	3	5	11
PACY	15,739	55.36	14.58	0	46.64	55.42	64.28	100

Control: SW=0								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
FORERR	155,560	1.92	4.67	0	0.14	0.51	1.58	35.09
RPA	155,560	0.51	0.50	0	0	1	1	1
MV	155,560	8.63	1.80	3.82	7.46	8.68	9.93	12.19
AF	155,560	18.93	9.53	1	11	19	26	61
INTA	155,560	20.3	20.31	0	2.16	13.62	33.72	77.43
MB	155,560	2.98	3.96	-8.58	1.15	2.01	3.53	26.44
RETVOL	155,560	0.02	0.01	0	0.01	0.02	0.02	0.06
LOSS	155,560	0.20	0.40	0	0	0	0	1
DECL	155,560	0.45	0.50	0	0	0	1	1
HOR	155,560	5.24	0.55	3.43	4.83	5.35	5.69	5.90
FEXP	155,560	1.40	0.79	0	0.78	1.39	1.99	3.11
GEXP	155,560	2.40	0.75	0	1.82	2.48	3.06	3.49
NUMCOM	155,560	15.2	8.54	1	9	13	20	45
NUMIND	155,560	3.47	2.20	1	2	3	5	11
PACY	155,560	53.92	11.37	0	47.27	54.24	60.79	100

Panel (B): Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	*FORERR*		**0.01**	**0.02**	**-0.30**	**-0.17**	**-0.19**	**-0.33**	**0.26**	**0.25**	**0.11**	**0.16**	**-0.04**	**-0.05**	**0.00**	**-0.03**	**-0.03**
(2)	*RPA*	**0.02**		0.00	0.00	**-0.03**	**0.01**	**-0.01**	**0.24**	**0.04**	**-0.05**	**-0.03**	**0.04**	**0.07**	**0.10**	**0.03**	**-0.06**
(3)	*SW*	**-0.02**	0.00		**-0.14**	**-0.17**	**0.09**	**0.07**	**-0.05**	**-0.08**	**-0.03**	**0.00**	**0.03**	**0.03**	**-0.17**	**0.09**	**0.03**
(4)	*MV*	**-0.29**	0.00	**-0.14**		**0.72**	**0.15**	**0.25**	**-0.47**	**-0.30**	**-0.03**	**-0.01**	**0.16**	**0.11**	**-0.01**	**-0.14**	**-0.02**
(5)	*AF*	**-0.16**	**-0.03**	**-0.17**	**0.71**		**0.05**	**0.03**	**-0.22**	**-0.11**	**0.04**	**0.01**	**0.17**	**0.09**	**0.02**	**-0.12**	**-0.02**
(6)	*INTA*	**-0.12**	**0.03**	**0.09**	**0.11**	0.00		**0.36**	**-0.19**	**-0.14**	**-0.01**	**0.01**	**0.03**	**0.07**	**-0.14**	**0.12**	0.00
(7)	*MB*	**-0.13**	**0.01**	**0.02**	**0.17**	**0.01**	**0.12**		**-0.27**	**-0.27**	**-0.10**	**-0.01**	**0.01**	**0.08**	**-0.05**	**0.12**	0.00
(8)	*RETVOL*	**0.32**	**0.20**	**-0.06**	**-0.49**	**-0.20**	**-0.17**	**-0.13**		**0.41**	**0.07**	**0.01**	**-0.09**	**-0.05**	**0.11**	0.00	**-0.01**
(9)	*LOSS*	**0.30**	**0.04**	**-0.08**	**-0.32**	**-0.10**	**-0.11**	**-0.13**	**0.47**		**0.24**	**0.00**	**-0.07**	**-0.07**	**0.07**	**-0.07**	**0.01**
(10)	*DECL*	**0.08**	**-0.05**	**-0.03**	**-0.03**	**0.04**	**-0.01**	**-0.08**	**0.08**	**0.24**		**-0.01**	**-0.01**	**-0.02**	**0.02**	**-0.03**	**0.00**
(11)	*HOR*	**0.06**	**-0.04**	**0.01**	**-0.01**	0.00	**0.01**	**-0.01**	**-0.02**	0.00	**-0.01**		**-0.02**	**-0.02**	**-0.02**	**0.00**	**0.00**
(12)	*FEXP*	**-0.04**	**0.04**	**0.03**	**0.17**	**0.17**	**0.01**	0.00	**-0.09**	**-0.07**	**-0.01**	**-0.02**		**0.44**	**0.10**	**0.04**	**0.02**
(13)	*GEXP*	**-0.05**	**0.06**	**0.02**	**0.12**	**0.10**	**0.06**	**0.04**	**-0.05**	**-0.06**	**-0.01**	**-0.02**	**0.46**		**0.19**	**0.13**	**0.01**
(14)	*NUMCOM*	**0.01**	**0.10**	**-0.16**	**-0.01**	**0.04**	**-0.13**	**-0.03**	**0.15**	**0.10**	**0.03**	**-0.02**	**0.09**	**0.21**		**0.33**	**-0.05**
(15)	*NUMIND*	**-0.04**	**0.03**	**0.09**	**-0.12**	**-0.11**	**0.08**	**0.04**	**-0.02**	**-0.07**	**-0.02**	0.00	**0.04**	**0.13**	**0.42**		**-0.05**
(16)	*PACY*	**-0.01**	**-0.06**	**0.04**	**-0.02**	**-0.02**	0.00	**0.01**	**-0.01**	**0.01**	0.00	**0.01**	**0.02**	0.00	**-0.06**	**-0.04**	

Panel (C): Results for analysts' forecast accuracy within the sample of analysts' entire firm coverage

Dependent variable: *FORERR*				
	Full sample			Restricted sample
Variables	i	ii	iii	iv
RPA	-0.092			
	(0.107)			
SW	0.049	0.061		
	(0.167)	(0.120)		
RPA × SW	-0.636***	-0.324**	-0.327*	-0.379*
	(0.156)	(0.142)	(0.157)	(0.181)
MV	-0.332***	-1.636***	-1.610***	-1.542***
	(0.039)	(0.181)	(0.186)	(0.212)
AF	-0.014**	-0.021	-0.020	-0.020
	(0.005)	(0.012)	(0.012)	(0.013)
INTA	-0.011***	-0.001	-0.000	-0.002
	(0.002)	(0.007)	(0.007)	(0.008)
MB	-0.064***	0.008	0.006	0.007
	(0.010)	(0.012)	(0.012)	(0.014)
RETVOL	78.227***	23.609**	23.157**	21.441**
	(8.992)	(8.031)	(7.926)	(9.739)
LOSS	1.975***	1.135***	1.139***	1.058***
	(0.155)	(0.124)	(0.122)	(0.144)
DECL	0.200***	0.336***	0.335***	0.366***
	(0.052)	(0.048)	(0.049)	(0.052)
HOR	0.546***	0.466***	0.471***	0.445***
	(0.064)	(0.032)	(0.030)	(0.033)
FEXP	0.108**	-0.015	-0.008	0.260*
	(0.042)	(0.016)	(0.020)	(0.135)
GEXP	0.011	-0.007	0.349	0.165
	(0.054)	(0.015)	(0.223)	(0.284)
NUMCOM	-0.018**	-0.001	-0.007*	-0.008
	(0.007)	(0.003)	(0.004)	(0.005)
NUMIND	-0.036	0.004	0.018	0.019
	(0.023)	(0.007)	(0.016)	(0.021)
PACY	-0.007**	-0.003**	0.003	0.004
	(0.002)	(0.001)	(0.002)	(0.002)
Observations	167,468	167,468	167,468	128,698
Adjusted R2	0.163	0.591	0.598	0.606
Firm FE	No	Yes	Yes	No
Analyst FE	No	No	Yes	No
Quarter FE	No	Yes	Yes	Yes
Firm × Analyst FE	No	No	No	Yes
No. of firms	3,590	3,590	3,590	2,560
No. of Swedish analysts	161	161	161	122
No. of non-Swedish analysts	1,212	1,212	1,212	969

Panel (D): Results for analysts' forecast accuracy within the sample of Swedish and non-Swedish analysts' mutual firm coverage

Dependent variable: *FORERR*				
	Full sample			Restricted sample
Variables	i	ii	iii	iv
RPA	-0.334**			
	(0.123)			
SW	-0.058	0.140*		
	(0.127)	(0.068)		
RPA × SW	-0.196	-0.279***	-0.262**	-0.319**
	(0.143)	(0.089)	(0.111)	(0.126)
MV	-0.745***	0.007	0.036	0.055
	(0.122)	(0.354)	(0.366)	(0.395)
AF	0.048***	-0.019	-0.016	-0.020
	(0.013)	(0.020)	(0.020)	(0.020)
INTA	-0.008***	0.028*	0.029*	0.027
	(0.002)	(0.014)	(0.014)	(0.017)
MB	-0.012*	0.003	0.002	0.003
	(0.006)	(0.003)	(0.004)	(0.003)
RETVOL	61.221***	9.420	8.070	4.474
	(13.175)	(8.798)	(8.527)	(8.397)
LOSS	0.221	0.332	0.395*	0.335
	(0.178)	(0.217)	(0.207)	(0.238)
DECL	-0.022	0.103**	0.110**	0.191***
	(0.061)	(0.044)	(0.045)	(0.055)
HOR	0.335***	0.336***	0.372***	0.317***
	(0.058)	(0.070)	(0.067)	(0.071)
FEXP	0.178***	0.014	0.008	0.158
	(0.041)	(0.015)	(0.030)	(0.195)
GEXP	-0.080*	-0.025	0.227	-0.099
	(0.045)	(0.021)	(0.238)	(0.361)
NUMCOM	0.008	0.006*	0.008	0.014
	(0.006)	(0.003)	(0.007)	(0.008)
NUMIND	-0.077**	-0.013	-0.024	-0.038
	(0.027)	(0.012)	(0.025)	(0.033)
PACY	-0.007**	-0.004**	0.003	0.002
	(0.003)	(0.002)	(0.002)	(0.003)
Observations	36,505	36,505	36,505	28,027
Adjusted R2	0.163	0.591	0.598	0.595
Firm FE	No	Yes	Yes	No
Analyst FE	No	No	Yes	No
Quarter FE	No	Yes	Yes	Yes
Firm × Analyst FE	No	No	No	Yes
No. of firms	223	223	223	188
No. of Swedish analysts	153	153	153	107
No. of non-Swedish analysts	864	864	864	541

Table 1.6: The test of the likelihood of analysts dropping firms in the post-RPA period

This table reports the results of the likelihood of Swedish analysts dropping firms in the post-RPA period, compared to non-Swedish analysts, which is conducted in a logistic model with the one-year-ahead forecasts provided by each analyst for each firm in the pre-RPA period. The dependent variable is an indicator variable – *DIS*, and equals to one when the analyst-firm pairs appear in the pre-RPA period but disappear in the post-RPA period, and zero otherwise. *FORERR* is the dependent variable, which is defined as analyst forecast error and calculated by taking the absolute value of the difference between the one-year-ahead EPS forecast and the actual EPS, scaled by the stock price two days before the forecast is provided, then multiplied by 100. *SW* is the indicator variable for the treatment group, equals to one for Swedish analysts, and zero for non-Swedish analysts. *RPA* is the indicator variable, equals to one when the observation is from post-RPA period (1 January 2015 onwards), and zero otherwise. *MV* represents the market value of equity in the logarithm form. *AF* is the total number of analysts following a firm within each quarter. *INTA* indicates the percentage of intangible assets scaled by total assets. *MB* is the market-to-book ratio and measured by dividing the market value of equity by the book value of equity. *RETVOL* is the stock return volatility within each quarter. *LOSS* is a dummy variable, and equals to one when the actual EPS is negative, and zero otherwise. *DECL* is a dummy variable, and equals to one when the current actual EPS is less than the EPS in the previous year. *FEXP* is the analyst's experience to a specific firm in the logarithm form. Analyst's experience to a specific firm is measured as the number of years since the analyst provides her first analyst's opinion on the specific firm to present. *GEXP* is analysts' general experience of being an analyst in the logarithm form. Analysts' general experience is measured as the number of years from when the analyst issued her first analyst's opinion for any firms to present. *NUMCOV* and *NUMIND* are total numbers of firms and industries that one analyst covers within each quarter respectively. Panel (B) reports Pearson (below diagonal) and Spearman (above diagonal) correlations. The correlations significant at the five percent level are shown in bold. Panel (C) outlines the results. All the regressions are clustered at the analyst level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
DIS	82,549	0.24	0.43	0.00	0.00	0.00	0.00	1.00
SW	82,549	0.09	0.29	0.00	0.00	0.00	0.00	1.00
FORERR	82,549	1.78	4.05	0.00	0.14	0.51	1.56	30.09
MV	82,549	8.55	1.80	3.83	7.42	8.59	9.80	12.17
AF	82,549	18.73	9.84	1.00	11.00	18.00	26.00	61.00
INTA	82,549	20.25	19.78	0.00	2.52	14.20	33.72	75.05
MB	82,549	2.96	3.70	-7.06	1.20	2.04	3.43	25.10
RETVOL	82,549	0.02	0.01	0.00	0.01	0.02	0.02	0.06
LOSS	82,549	0.17	0.38	0.00	0.00	0.00	0.00	1.00
DECL	82,549	0.47	0.50	0.00	0.00	0.00	1.00	1.00
FEXP	82,549	1.37	0.77	0.00	0.78	1.34	1.95	3.05
GEXP	82,549	2.35	0.76	0.00	1.74	2.42	3.03	3.46
NUMCOM	82,549	13.89	7.91	1.00	8.00	12.00	18.00	41.00
NUMIND	82,549	3.46	2.19	1.00	2.00	3.00	5.00	11.00

Panel (B): Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	*DIS*		**0.02**	**0.11**	**-0.12**	**-0.11**	**0.01**	**-0.06**	**0.05**	**0.04**	**0.03**	**-0.16**	**-0.15**	**-0.03**	**0.00**
(2)	*SW*	**0.02**		**0.05**	**-0.14**	**-0.18**	**0.09**	**0.05**	**-0.03**	**-0.06**	**-0.01**	**0.04**	**0.03**	**-0.17**	**0.08**
(3)	*FORERR*	**0.08**	**0.01**		**-0.30**	**-0.19**	**-0.15**	**-0.31**	**0.24**	**0.25**	**0.11**	**-0.05**	**-0.06**	**-0.03**	**-0.03**
(4)	*MV*	**-0.14**	**-0.15**	**-0.29**		**0.78**	**0.11**	**0.23**	**-0.52**	**-0.33**	**-0.02**	**0.15**	**0.14**	**-0.01**	**-0.13**
(5)	*AF*	**-0.11**	**-0.17**	**-0.18**	**0.76**		**0.05**	**0.06**	**-0.31**	**-0.17**	**0.05**	**0.17**	**0.12**	**0.01**	**-0.12**
(6)	*INTA*	**0.01**	**0.09**	**-0.10**	**0.07**	0.00		**0.32**	**-0.14**	**-0.12**	**0.03**	**0.04**	**0.06**	**-0.15**	**0.12**
(7)	*MB*	**-0.05**	**0.02**	**-0.13**	**0.15**	**0.02**	**0.08**		**-0.20**	**-0.21**	**-0.09**	**0.03**	**0.09**	**-0.02**	**0.12**
(8)	*RETVOL*	**0.07**	**-0.05**	**0.29**	**-0.51**	**-0.28**	**-0.12**	**-0.08**		**0.39**	**0.05**	**-0.12**	**-0.08**	**0.06**	**0.01**
(9)	*LOSS*	**0.04**	**-0.06**	**0.32**	**-0.35**	**-0.16**	**-0.09**	**-0.09**	**0.46**		**0.19**	**-0.06**	**-0.08**	**0.04**	**-0.07**
(10)	*DECL*	**0.03**	**-0.01**	**0.08**	**-0.01**	**0.05**	**0.03**	**-0.08**	**0.05**	**0.19**		**-0.02**	**-0.03**	**-0.01**	**-0.05**
(11)	*FEXP*	**-0.16**	**0.05**	**-0.04**	**0.16**	**0.17**	**0.03**	**0.01**	**-0.12**	**-0.06**	**-0.02**		**0.43**	**0.09**	**0.05**
(12)	*GEXP*	**-0.16**	**0.03**	**-0.05**	**0.14**	**0.12**	**0.06**	**0.04**	**-0.08**	**-0.07**	**-0.02**	**0.45**		**0.19**	**0.12**
(13)	*NUMCOM*	**-0.03**	**-0.16**	**-0.02**	**-0.01**	**0.03**	**-0.14**	**-0.03**	**0.08**	**0.05**	**-0.01**	**0.08**	**0.20**		**0.32**
(14)	*NUMIND*	0.00	**0.08**	**-0.04**	**-0.11**	**-0.12**	**0.08**	**0.05**	**-0.03**	**-0.07**	**-0.04**	**0.05**	**0.12**	**0.42**	

Panel (C): Regression results

Dependent variable: Pr(*DIS*=1)			
Variables	i	ii	iii
SW	0.155	0.034	-0.240
	(0.196)	(0.192)	(0.253)
FORERR	0.040***	0.018**	0.000
	(0.006)	(0.008)	(0.006)
SW × *FORERR*	0.006	0.009	0.013
	(0.017)	(0.015)	(0.023)
MV		-0.103*	-0.115
		(0.061)	(0.087)
AF		-0.005	0.028***
		(0.009)	(0.008)
INTA		0.004	0.007
		(0.002)	(0.006)
MB		-0.017*	0.020***
		(0.010)	(0.007)
RETVOL		3.097	2.432
		(4.506)	(3.218)
LOSS		-0.074	0.143*
		(0.111)	(0.083)
DECL		0.118*	-0.056
		(0.061)	(0.050)
FEXP		-0.344***	-0.461***
		(0.059)	(0.070)
GEXP		-0.289***	-0.274***
		(0.080)	(0.093)
NUMCOM		0.009	0.025**
		(0.015)	(0.012)
NUMIND		0.008	-0.027
		(0.044)	(0.043)
CONSTANT	-1.258***	1.151***	1.688
	(0.083)	(0.447)	(1.278)
No. of Ob.	82,549	82,549	66,702
Pseudo R-squared	0.006	0.101	0.217
Firm Fixed Effect	No	No	Yes
Quarter Fixed Effect	No	Yes	Yes

Table 1.7: Market reaction to forecast revisions

This table reports the results of the change in the market reaction to forecast revisions with the RPA adoption. The analysis is on the firm-day basis among the Swedish firms followed by at least one analyst. The dependent variable, *ABS_ABRET*, is the size-adjusted absolute abnormal return in the percentage form. *RPA* is the indicator variable, equals to one for the post-RPA period (1 January 2015 onwards), and zero otherwise. *PRE* is the indicator variable, equals to one from 1 January 2014 onwards, and zero otherwise. *ANALYST* is the dummy variable, with the value of one if any analyst provides forecast revisions on the day or the next day ([0, +1]), and zero otherwise. *EARN* is the dummy variable, with the value of one if a firm makes an earnings announcement on the day or the next day ([0, +1]), and zero otherwise. Panel (A) presents descriptive statistics for variables used in the regression. Panel (B) reports the results. All regressions are clustered at the firm and day levels. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

Variable	n	Mean	S.D.	Min	0.25	Median	0.75	Max
ABS_ABRET	276,137	1.43	1.57	0.00	0.42	0.94	1.84	9.14
RPA	276,137	0.54	0.50	0.00	0.00	1.00	1.00	1.00
PRE	276,137	0.79	0.41	0.00	1.00	1.00	1.00	1.00
ANALYS	276,137	0.13	0.33	0.00	0.00	0.00	0.00	1.00
EARN	276,137	0.02	0.14	0.00	0.00	0.00	0.00	1.00

Panel (B): Regression results

	i	ii	iii	iv
ANALYST	0.13***	0.15***	0.11***	0.15***
	(0.02)	(0.02)	(0.03)	(0.02)
EARN	1.42***	1.44***	1.43***	1.45***
	(0.07)	(0.07)	(0.10)	(0.09)
RPA × *ANALYST*	0.11***	0.06***	0.10***	0.07***
	(0.03)	(0.02)	(0.03)	(0.02)
RPA × *EARN*	0.00	0.01	0.01	0.03
	(0.08)	(0.08)	(0.09)	(0.09)
PRE × *ANALYST*			0.02	-0.00
			(0.03)	(0.03)
PRE × *EARN*			-0.02	-0.03
			(0.12)	(0.11)
Observations	276,137	276,137	276,137	276,137
Adjusted R-squared	0.172	0.208	0.172	0.208
Firm FE	Yes	No	Yes	No
Firm × Quarter FE	No	Yes	No	Yes
Day FE	Yes	Yes	Yes	Yes
No. of days having *ANALYST* before RPA	9,422			
No. of days having *ANALYST* after RPA	11,412			
No. of days having *EARN* before RPA	1,248			
No. of days having *EARN* after RPA	1,364			
Number of unique firms before RPA	309			
Number of unique firms after RPA	337			

Chapter 2

Broker-hosted credit investor conferences: Evidence from the corporate bond market

2.1 Introduction

The extant literature has documented the effects of various forms of direct interactions between firm managers and investors in the stock market. For example, conference presentations, roadshows, and Analyst/Investor days are found to elicit significant stock market reactions and analyst forecasting activities, and firms that engage in such direct interactions experience an increase in analyst following and in equity institutional investor holding, as well as a decrease in the cost of equity and in the bid-ask spread of the stock. (Bushee et al. 2011; Green et al. 2014a; Green et al. 2014b; Markov et al. 2017; Bushee et al. 2018; Kirk and Markov 2016). However, we have little knowledge with regards to the effects of such direct interactions on the credit investors, the other important financier in the capital market. These direct-interaction events are alternative forms of voluntary disclosure (Bushee et al. 2011). Firm managers that co-locate with investors at the same place may disclose the firm-specific information tailored to the investors.[45] Thus the type of investors participating in the events may determine the type of information disclosed by firm managers. If an event attracts mainly credit investors, we then expect that the information would be more likely to be credit risk related due to credit investors' non-linear payoff determined by the probability of default (Merton 1974). In this paper, we focus on a typical direct-interaction event, broker-hosted conferences, and investigate the impact of broker-hosted conferences on the corporate bond market, in particular, when conferences are organized for credit investors mainly.

Broker-hosted conferences are a type of research service provided by brokerage houses to the institutional investors (Brown et al. 2016). These conferences are invitation-only events where presentations, discussions, and face-to-face private meetings with firm managers would occur (Green et al. 2014a). Most of the

[45] Under the Regulation Fair Disclosure, material private information is prohibited to be selectively disclosed. However, firm managers can still disclose non-material information in these events. Koch et al. (2013) provides a review of Regulation Fair Disclosure.

conferences are organized with an industry theme, such as the Healthcare Conference, or the Basic Materials Conference, where firms from the same industry are invited to present during the conference (Bushee et al. 2011). However, we have identified a subset of broker-hosted conferences that are credit investment oriented, rather than industry specific, such as the J.P. Morgan High Yield Leveraged Finance Conference, or the Bank of America Merrill Lynch Credit Conference. We label this type of conference as the credit conference and the remaining are the non-credit conferences. In either type of conferences, the hosting brokers determine the invitation of the audience and the presenting companies. If a conference is credit investment oriented, the host would be more likely to invite credit investors to attend. In this regard, we argue that the presenting firm managers would disclose more information related to firms' credit risk within such environment where the most audience are credit investment driven.

At the outset, we study the determinants of firms attending credit conferences. First, we find that firms with a higher likelihood of financial distress are more likely to attend credit conferences. Merton (1974) suggests that the sensitivity of debt price to the changes of the firm value increases with the firm's financial distress. On the account of non-linear payoff of the debt, credit investors are more demanding to a firm's information when the firm is in a state of financial distress. On the other hand, from the perspective of the brokerage house that organizes credit conferences, higher demand from investors may bring more trading transactions and commissions when the firm is in the financial distress. Second, we find that firms with a greater amount of public debt outstanding attend more credit conferences, as the demand for the credit information increases with the amount and the number of the public debt (Gurun et al. 2016). Third, we find that firms with greater debt financing intention attend more credit conferences as the disclosure during the credit conference may help achieve a reduction in the cost of capital (Green et al. 2014a).

Next, we turn to explore how the corporate bond market reacts to credit conferences, as well as to non-credit conferences. We focus on a large sample of publicly-traded, non-financial, and non-utility firms with the bond trading data available from 2005 to 2016. We find a significant abnormal return around both credit conferences and non-credit conferences, but the economic magnitude of the credit conferences is larger than that of the non-credit conferences. Specifically, we find that the mean of abnormal return is 12.27 basis points (bps) to credit conferences and only 2.01 bps to non-credit conferences. Given that firms with speculative-grade credit ratings and short time-to-maturity of bonds outstanding are more willing to attend credit conferences, we further find that the mean of the abnormal return to credit conferences is only significant when bonds have speculative grades or short time-to-maturity.

In line with the abnormal return test, we next use trading volume as the measure of the bond market reaction. We use the same sample as in the abnormal return test and conduct the trading volume test in the panel regression. After controlling for other events that affect the bond trading volume, we find an incremental 0.14% of bonds' principal traded over the six-day window, starting from the credit conference day to the next five trading days. The economic magnitude of the trading volume to the credit conference is similar to the provision of analysts' sell recommendations. Furthermore, we find that the trading volume on the credit conference window is larger for the firms with speculative grades than that with investment grades. In contrast, we do not find any significant change in the trading volume when non-credit conferences occur.

Classical finance theory suggests that firms' cost of capital is positively associated with information asymmetry (Leland and Pyle 1977; Stiglitz and Weiss 1981; Diamond 1985). As a type of voluntary disclosure, firms attending general broker-hosted conferences experience a decrease in cost of equity (Green et al. 2014a). Analogously, we expect firms attending credit conferences may also experience a reduction in the cost of debt. We use monthly yield spread from the secondary bond market as a proxy of the cost of debt (Campbell and Taksler 2003; Chen et al. 2007; Huang and Huang 2012; Amiraslani et al. 2017). Then we test whether the yield spread decreases in the months after firms' conference attendance. The result supports credit conferences but not non-credit conferences. Specifically, we use the change in the yield spread from the previous three months to the next three months as the dependent variable and find the yield spread decreases by 19.5 bps after the firm attends a credit conference. We do not find any reduction in cost of debt for firms' non-credit conference attendance.

Lastly, we examine whether the bond institutional investor ownership changes with firms' conference participation. We find that the overall bond institutional ownership increases by 0.42% when a firm attends a credit conference and such increase is mainly attributed to the mutual fund investors. We do not find any changes in insurance companies' bond ownership. Moreover, we split the sample by bonds' credit rating (investment grades versus speculative grades). We find that the significant increase in the mutual fund ownership is mainly from the speculative grade bonds, rather than the investment grade bonds. Similar to the previous section, we do not find any significant results on the non-credit conferences.

We make following contributions to the literature. Firstly, we contribute to the voluntary disclosure literature. Numerous papers investigate the effects of voluntary disclosure on the cost of equity (Francis et al. 2008; Dhaliwal et al. 2011; Baginski and Rakow 2012), but there is no evidence whether credit investors or cost of debt are affected by voluntary disclosure, as the information disclosed voluntarily such as management forecasts is more likely to affect the wealth of equity investors, rather than credit investors. By studying broker-hosted credit conferences, where managers voluntarily disclose information tailored to credit investors, we find that voluntary disclosure, in this specific setting, affects cost of debt and bond institutional investor ownership. Secondly, our work complements the findings in Green et al. (2014a) and Bushee et al. (2011), who investigate the effects of conference presentations from the equity investor's perspective. We show that the corporate bond market and credit investors also react to conferences, especially the credit conference. Thirdly, we also contribute to the analyst research service literature. Papers such as Maber et al. (2016), Brown et al. (2015 and 2016) document the importance of the corporate access service provided by sell-side analysts to the equity investors. Our paper suggests such service is also valuable to credit investors, in particular when the service is tailored to them.

The remainder of the paper proceeds as follows. Section 2 reviews the literature and propose hypothesis. In Section 3, we describe the data collection and discuss the general sample statistics. Section 4 investigates the determinants of firms attending credit conferences. Sections 5 and 6 present the results of the bond market reactions to the conferences by using abnormal return and trading volume as the separate measures. In Section 7, we examine the change in the cost of debt of firms attending the conferences, whilst Section 8 reports the change in the bond institutional investor ownership around the conference quarters. Section 9 concludes the paper.

2.2 Data collection and general sample description

In this section we present the data collection process. The key variable is whether and when a firm attends a broker-hosted conference and the type of the conference. Following Green *et al.*, (2014), we obtain the data of broker-hosted conferences from the Bloomberg Corporate Events Database for a period from 2005 to 2016.[46] Table 2.1 reports the general data description. As reported in Panel (A), we initially obtained 237,528 firm-conference observations. We manually deleted the conferences that are non-broker hosted or have no host names, or those whose Bloomberg tickers cannot be converted into 9-digit *cusip*, as well as non-conference events such as non-deal roadshows, analysts' field trips, or Analyst/Investor days that are mistakenly classified by Bloomberg. This leaves us with 160,184 firm-conference observations remaining in the sample. Next, we identify credit conferences by finding the following key words in the conference name: "fixed income", "credit", "high-yield", "yield", "bond", "debt", and "loan".[47] We label the remaining conferences as the non-credit conferences. We successfully identified 4,380 firm-credit-conferences, and 155,804 firm-non-credit-conferences. Within the 160,184 firm-conference observations, there are 7,144 unique companies, among which 2,227 companies have in total 17,935 bonds outstanding during the sample period. Panel (B) presents the conference attendance within each year. With respect to credit conferences, there are on average 365 firm-conferences, 230.8 unique firms, and 12.5 unique conferences per year, which indicates one firm attends on average 1.58 credit conferences per year and each conference has 29.2 firms attending. In addition, the average numbers of unique brokers are 8.5, suggesting one credit-conference hosting broker organize 1.47 credit conferences within a year. Turning to non-credit conferences, the statistics is much larger than credit conferences. There are on average 12,983.7 firm-conferences, 3,119.1 firm-years, 598.3 unique conferences, and 117 unique brokers within each year, indicating one firm attending 4.2 non-credit conferences per year and each conference has 21.7 firms attending. Panel (C) reports the names of the conference-hosting brokerage houses. Over the 12-year sample period, there are 150 credit

[46] The 12-year sample period is chosen to match the availability of the data from other sources (e.g. TRACE).

[47] As the word "credit" is also part of the name of "Credit Suisse" and "Crédit Agricole". We carefully read the title of the conferences hosted by these two brokerage houses and make sure that they are truly credit conferences.

conferences, among which 135 credit conferences are hosted by the major 15 brokers. Deutsche Bank and J.P. Morgan are the top hosting brokers. They host on average one credit conference each year and over 60 firms attending each credit conference. We also report the descriptive statistics of the credit-conference-brokers hosting non-credit conferences. The top credit conference hosting brokers, Deutsche Bank and J.P. Morgan, do not dominate the market anymore. They host 239 and 248 non-credit conferences in total (around 20 conferences each year), and less than 30 firms attend each conference.

2.3 Determinants of firms attending non-credit and credit conferences

In this section we investigate the determinants of firms' attendance of credit conferences and non-credit conferences. In the fourth section of Green *et al.*, (2014), they investigate the determinants of broker-hosted conferences, regardless of non-credit or credit conferences. As the majority of the conferences are non-credit, the results from Green *et al.*, (2014) would be similar to our results for the non-credit conference. Thus, we mainly focus on the credit conference determinants in this paper.

We firstly hypothesize the major factor driving a firm to attend credit conferences is the firm's probability of financial distress. Merton (1974) suggests that the value of the firm information to debt investors increases with the probability of financial distress. When a firm is in financial distress, the demand for the firm's information would be great. We use financial leverage (total liabilities over total assets), Altman Z-score, and firms' distance to default as the proxies of the likelihood of financial distress. Financial leverage is an intuitive measure for the financial distress, and firms with high financial leverage have a high likelihood of financial distress. Altman Z-score considers balance sheet liquidity when measuring financial distress (Altman 1968; Altman 2000). The distance to default measures corporate default risk, which combines financial leverage and asset volatility (Duan and Wang 2012; RMI 2012; Florou and Kosi 2015). Then we expect that firms with higher financial leverage, lower Altman Z-score, and lower distance to default will have greater financial distress. Moreover, we include cash ratio (cash holding over total assets) as an important control variable for the regression. Intuitively, we would expect that higher cash holdings should be "safer" and related to lower financial distress. However, Acharya et al. (2012) argue that a conserve cash policy is more likely to be adopted by a firm with a higher likelihood of financial distress, as the firm may use cash holding as a safety cushion for the credit investors. Hence we do not expect the sign of the estimated coefficient on cash holding. Second, we expect that firms with a great amount of public debt outstanding would attend more credit conferences. Similar to Johnston et al. (2009) where they find sell-side debt analysts write more reports for companies with more debt, we argue that the demand for the credit information increases with the amount of public debt. We directly measure the amount of public debt by calculating the total amount and the total number of public bond outstanding for a firm within a year. We also create a dummy variable for firms without any debt as the extreme case for the amount of public debt. Then we expect positive coefficients on the amount and the number of the public debt outstanding, as well as a negative coefficient on the "no bond" dummy. The third determinant for firms attending credit conferences we expect is the needs of debt refinancing. Copious literature has documented a positive association between the information asymmetry and the cost of capital.[48] Firms with greater debt refinancing needs may be more likely to attend credit conferences, as such conferences are an alternative mechanism of voluntary disclosure, which may lead to a reduction in the information asymmetry between the firm and the (potential) credit investors. We use the average time-to-maturity of all bonds outstanding for a firm within a year as a proxy for the firm's debt refinancing intention. We expect that firms whose bonds have lower time-to-maturity may have a higher intention to refinance their debt and then have a higher chance of attending credit conferences. Lastly, we expect that firms with a credit rating just below the lowest investment grade (which is the highest speculative grade) have a higher likelihood of attending credit conferences.[49] Firms with a credit rating on the "C" level are very close to default. Thus, investors may not demand the information disclosed by firms with deeply speculative grades. We use the Standard & Poor credit rating, and assign a firm to the "just below" category if the firm's average credit rating of all bonds outstanding is within a range of BB and BB+. We also include other firm fundamental variables in the model as control variables, which are intangible assets over total assets, market adjusted stock return volatility, market to book ratio, market value of equity in the natural logarithm form, analyst following, as well as the number

[48] See Healy and Palepu (2001) for the literature review.

[49] For example, Standard & Poor's defines bonds with credit ratings above BBB- (including BBB-) as the investment grade bonds, and the remaining as the speculative grade bonds.

and the percentage of equity institutional investor ownership. Lastly, we control for the mutual fund bond ownership and insurance company bond ownership separately, rather than the total bond institutional investor ownership as these two types of investors dominate in the bond market and have different trading incentives due to different regulatory constraints (Dass and Massa 2014).

We use a multinomial logit model to investigate the determinants of firms attending credit conferences within a sample of non-financial and non-utility firms from 2005 to 2016. In particular, we define a nominal variable $CONF_{it}$ as the dependent variable in the following model:

$$\Pr(CONF_{it} = \mathrm{j}|\mathbf{x}_{it}) = \frac{\exp(\boldsymbol{x}'_{it}\boldsymbol{\beta}_j)}{\sum_{j=0}^{2}(\boldsymbol{x}'_{it}\boldsymbol{\beta}_j)'} \tag{2.1}$$

where *j* takes value of zero if firm *i* does not attend any conference in year *t*, value of one if firm *i* attends at least one non-credit conference but no credit conference in year *t*, value of two if firm *i* attends at least one credit conference but no non-credit conference in year *t*, and value of three if firm *i* attends both credit and non-credit conferences in year *t*. The independent variable vector $\boldsymbol{x}_{it}$ includes financial leverage (*LEV*), Altman Z-score (*ZSCORE*), and distance to default (*DISTA_DEFT*) for measuring the probability of financial distress; the dummy variable for no bond outstanding (*NOBOND*), as well as the total offering amount and the total number of public bond outstanding (*OABD*, *NUMBD*) for measuring investors' credit information demand; and the average time-to-maturity of all bonds outstanding (*MAT*) for the measure of firms' debt refinancing intention. Other control variables include cash ratio (*CASH*), the dummy variable of just below investment grade cutoff (*JUSTBELOW*), the percentage and the number of equity institutional investors (*INSTEQ* and *NUMEQ*), as well as bonds' insurance company ownership and mutual fund ownership (*INSTBD_INS* and *INSTBD_MUT*). We also include other firm-level control variables such as the market value of equity in the logarithm form (*MVE*), intangible assets scaled by total assets (*INTA*), the market-to-book ratio (*MB*), and analyst following (*AF*). All variables, with an exception of *NOBOND*, are one year lagged and winsorized at 1% and 99% levels.

Panel (A) of Table 2.2 reports the sample creation for the multinomial regression analysis. Column (i) reports the numbers of firm-years from Bloomberg that attend non-credit conferences only (*CONF*=1), credit conferences only (*CONF*=2), and both conferences (*CONF*=3) respectively.[50] We merge the conference data with the entire COMPUSTAT within the sample period from 2005 to 2016. Then in column (ii) we find 30,277 (44.3%) firm-years attending non-credit conferences only, 205 (0.3%) firm-years attending credit conferences only, 2020 (3.0%) firm-years attending both credit and non-credit conferences, and the remaining 35,823 (52.4%) firm-years do not attend any conferences. After excluding financial and utility industries, as well as missing data, we have 25,908 firm-year observations remained (column iv). The proportion of non-credit conferences only increases to 67.6%, as opposed to the no conference percentage declining to 27.2%. The credit-conference-related firm-year percentages (*CONF*=2 and *CONF*=3) increase slightly. Panel (B) of Table 2.2 presents the data description within each category of conference attendance. The variable statistics, except analyst following, between the credit-conference only group (*CONF*=2) and the both conference group (*CONF*=3) are very similar, compared to the non-credit conference group (*CONF*=1) or the no conference group (*CONF*=0). Specifically, the two credit conference related groups (*CONF*=2 and *CONF*=3) have higher financial leverage, lower Altman Z-score, lower distance-to-default, more bonds outstanding, and higher mutual fund investor ownership than the other two groups (*CONF*=1 and *CONF*=0).

The results of estimating the multinomial model are reported in Panel (C) of Table 2.2. Columns (i), (ii), and (iii) present the results when we choose firms that do not attend any conference within a year as the benchmark group (*CONF*=0), whilst the results in columns (iv) and (v) are based on the benchmark group of firms attending non-credit conferences only (*CONF*=1). Results are largely consistent with our expectations. Regarding the determinant of the probability of financial distress, in the estimation where no-conference firms are the benchmark, columns (ii) and (iii) show that the estimated coefficients for Altman Z-score and the distance to default are negatively significant, indicating firms with lower Altman Z-score and distance to default are more likely to participate in credit conferences. The positive coefficient on financial leverage suggests that more financially leveraged firms have a higher likelihood of attending credit conferences. With respect to the participation of non-

[50] The total number of the non-credit conference firm-year is equal to 37,429 (35,140 plus 2,289); and the total number of the credit conference firm-year is equal to 2769 (480 plus 2,289). These two figures are the same to the total firm-year number in Panel (B), Table 2.1.

credit conferences, financial distress seems inclusive as a determinant. In column (i), the estimated coefficients for the different financial distress measures are contradictory. The negative coefficient on the financial leverage implies that firms with a lower probability of financial distress attend more non-credit conferences, whereas the negative coefficients on Altman Z-score and the distance to default ratio suggest the opposite. This finding confirms our expectation that financial distress is the determinant of a firm attending credit conferences, but not non-credit conferences. Next, the deeply negatively significant coefficients on the *NOBOND* in columns (ii) and (iii) indicate that the demand for credit information are less when the firm has no debt. The amount and the number of public debt outstanding are insignificant, which are inconsistent with our expectation. But they turn to significant with the predicted signs in column (v) when we use the non-credit conference only as the benchmark. Furthermore, we find that the average time-to-maturity is negatively associated with the likelihood of attending credit conferences, indicating that firms with higher debt refinancing intention are more likely to attend credit conferences. Lastly, the coefficient on *JUSTBELOW* is highly positive and significant in column (iii), which suggests that firms whose credit rating is just below the cutoff of the investment/speculative grades have higher likelihood to attend credit conferences than firms with either deeply speculative grades or investment grades. However the coefficient for the credit conference-only model in column (ii) is insignificant. This may be due to the insufficient number of firms only attending credit conferences (less than 0.5% shown in Panel (B)). Turning to models where we use non-credit conferences only as the benchmark in columns (iv) and (v), the result is very similar to the estimation in columns (ii) and (iii). In addition, we restrict the sample to firms having at least one bond outstanding within a year and replicate model (1). Panel (E) presents the results and they are qualitatively unchanged.[51]

In sum, the determinants of firms attending credit conferences are different to the non-credit conference attendance documented in Green et al. (2014). Firms in the greater financial distress, with more public debt outstanding and with short time-to-maturity on average are more likely to attend credit conferences than their counterparts.

[51] Within the restricted sample, we do not control for industry fixed effect as the sample size is not large enough for the inclusion.

2.4 Using abnormal return as the measure of the bond market reaction

In this section, we investigate the bond market reaction to both credit and non-credit conferences by using bonds' abnormal return. To construct treatment group, we begin with 2,227 conference-attending companies with at least bond outstanding during the sample period from 2005 to 2016. We only focus on bonds whose issuers are non-financial and non-utility firms. Then we search Mergent FISD for bonds' issuing information including the issuer's identifier (6-digit *cusip*), offering date and amount, maturity, coupon rate, frequency of interest payment etc. Consistent with Bessembinder et al., (2009) and May (2010), we exclude putable, preferred, convertible and exchangeable issues, and foreign currency, Yankee and Canadian bonds, as well as bonds with varying or zero coupon rate. We also drop private placement and perpetual issues, and bonds whose principal is not $1000, or the "day count basis" is not "30/360". We only keep bonds whose interest payment frequency within a year is 1, 2, 4, or 12.[52] We further exclude bonds that are matured before January 1st 2005, and offered after December 31st 2016 as those issues are not within our sample period. To ensure that a bond's accrued interest (for calculating the dirty price) and time-to-maturity can be calculated, we further require that several bonds' attributes must be available, including coupon rate, interest payment frequency, as well as offering and maturity date. Finally, we drop bonds that do not exist on the conference dates.[53] Panel (A) of Table 2.3 reports the filtering process and the number of treated bond candidates. We start from 17,935 bonds and 2,227 companies. After applying aforementioned restrictions, we have 7,556 bonds (1,037 companies) remained.

Second, we use issuer identifiers (the first 6 digits of *cusip*) to merge the remaining 7,556 bonds with the conference data collected from Bloomberg to construct a bond-day panel as the treatment group. As shown in Panel (B) of Table 2.3, we obtained 187,468 bond-conference-day observations. Furthermore, we delete bond-dates whose credit rating is not available or in default, as well as the time-to-maturity is over 30 years. Then we have 166,762 bond-dates remained in the sample, among which there are 6,976 bonds issued by 993 companies (Panel B of Table 2.3). With respect to the

[52] Issues that we delete either have no interest payment frequency, or have a frequency of 99, which is highly likely to be an error in Mergent FISD.
[53] These bonds are the issues matured before the conference or offered after the conference. But they do appear in the other time of the year.

control group, we use all the bonds (after applying the treated bonds' filtering criteria) in Mergent FISD whose issuers do not attend any conferences on the conference dates as the candidates for the control group.[54]

Third, we obtain bonds' clean price from the enhanced TRACE. We use the algorithm from Dick-Nielsen (2009 and 2013) to clean the data. Specifically, we delete trade cancellations and corrections, and when multiple trades' price, volume, yield, and transaction time are exactly the same, we discard all but keep one transaction.[55] [56] As the bond price in TRACE (and enhanced TRACE) includes transaction cost and such cost varies with the size of the trade, which makes the price in TRACE less accurately reflect the underlying value of the bond (Edwards et al. 2007). We use the "trade-weighted price, all trades" approach suggested in Bessembinder et al., (2009) to aggregate the bond price to the daily level. This approach assigns higher weights to larger trades, which could reduce the noise of the transaction cost on small trades.

Fourth, we use both clean price and dirty price to calculate bond return. The dirty price equals the clean price plus the interest accrued since the last interest payment date. In line with Bessembinder et al. (2009), May (2010), and Ederington et al. (2015), we calculate bond return by using dirty price and clean price as follows:

$$BRET\_D_{it} = \frac{(P_{i,t+1} + AI_{i,t+1}) - (P_{i,t-1} + AI_{i,t-1})}{P_{i,t-1} + AI_{i,t-1}} \tag{2.2}$$

$$BRET\_C_{it} = \frac{P_{i,t+1} - P_{i,t-1}}{P_{i,t-1}} \tag{2.3}$$

where $BRET\_D_{it}$ ($BRET\_C_{it}$) is the bond return calculated by using dirty (clean) price for bond *i* on day *t*;[57] P_{t+1} (P_{t-1}) is the clean price one trading day after (before) the conference, where subscript *t* indicates the conference date;[58] AI_{t+1} and AI_{t-1} are the

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[54] Furthermore, to mitigate the information leaking prior to the conference and the delay of market reaction to the treated bonds, we also exclude ten-day observations of the treated bonds before (and after) the conference date when creating the control group. Therefore, 21-day bond observations that are centered on the conference date are deleted in the control group.
[55] These trades are highly likely the pass-through transactions. (Becker and Ivashina 2015).
[56] We also use the uncleaned enhanced TRACE data to aggregate the daily bond price, and the result is almost identical.
[57] In the bond level study, the firm subscript *j* is compressed.
[58] The reason that we use P_{t+1} instead of P_t as the post-conference bond price is similar to the explanation in Ederington et al. (2015). The bond price is the weighted average price throughout a day, rather than the bond closing price at the end of the day, and conference presentations may occur before, during, or after the trading on day *t*. Then the P_t may not capture the information revealed from the conference.

interest accrued to day *t+1* and *t-1* respectively, from the last interest payment day. As the bond market is highly illiquid, we may not have bond transactions on day *t+1* and day *t-1*. Thus we create three sets of returns. Firstly, we only keep those bonds that have transactions (and price) on day *t+1* and *t-1*, and use them to calculate bond return. We use a suffix "*_m1p1*" to specify this set of return (*BRET_D_m1p1* and *BRET_C_m1p1*). This approach has the least noise in the return but reduces the sample size severely. Secondly, when P_{t-1} is not available, we use the last available daily price up to five trading days prior to the conference date as the substitute of P_{t-1}; and when P_{t+1} is not available, we use the first available daily price within five trading days after the conference. We discard the bonds when P_{t-1} or P_{t+1} cannot be found within such ten-day period. We label this set of return as *BRET_D_m5p5* and *BRET_C_m5p5*. The third method is analogous to the second, except we extend to ten trading days before and ten trading days after the conference to find substitutes for P_{t-1} and P_{t+1}. We name this set of return as *BRET_D_m10p10* and *BRET_C_m10p10*. We do not further extend the pre- and post-conference days to mitigate the concern of including stale price.

Fifth, we follow the matching portfolio method in Bessembinder et al., (2009) to calculate a bond's abnormal return around a conference. We match each treated bond with the bonds from the control group with the similar credit rating, time-to-maturity, and industry on each conference date (Klein and Zur 2011). More specifically, we follow Baghai et al. (2014) to combine all the "+" and "–" in Standard & Poor's credit rating with the middle rating, and create seven rating classes: AAA/AA, A, BBB, BB, B, CCC, and CC/C. Next, within each credit rating class, we split the sample into two maturity bands based on the time-to-maturity of each treated bond on the conference day (Bessembinder et al. 2009; Ederington et al. 2015; May 2010). In particular, for the classes CCC, the two bands are below four years, and four years and above. For the class AAA/AA, the two bands are below five years, and five years and above. For the remaining classes, the two bands are below six years, and six years and above. We do not partition the CC/C class as there are too few observations. This classification ensures that the number of treated bonds within each maturity band and each credit rating class are roughly equal. Finally, we match each treated bond with the bonds in the control group with the same credit rating class, time-to-maturity group, and industry. As one treated bond can have multiple matched bonds in the control group, we calculate the value-weighted return of matched bonds in the control group by using the market value of each bond on the previous day of the conference, so that each treated bond return (*TBRET*) has one aggregated matched bond return (*CBRET*) from the control group. Then the abnormal return for each treated bond (*ABRET*) is the difference between *TBRET* and *CBRET*. Panel (C) of Table 2.3 presents the final abnormal return sample under each return group. Specifically, we 43,490, 84,107, and 93,729 bond-day observations for the *_m1p1*, *_m5p5*, and *_m10p10* groups respectively. The total number of treated bond-conference-day candidates is 166,762, which is the number before adding the bond price and the control group. This suggests that only 26%, 50%, and 56% remained in the *_m1p1*, *_m5p5*, and *_m10p10* groups respectively with a valid abnormal return.

We present the results on the bond level and the firm level respectively. On the bond level, one firm can have multiple bonds outstanding at the same time so that the standard error is biased. To mitigate such concern, we cluster the standard errors by firms when conducting mean tests. Panel (D) of Table 2.3 reports the means of the raw return for the treatment group and the control group respectively.[59] For the credit conferences, the means of the raw returns in the treatment group are all positively significant. This compares to the insignificant raw returns in the control group. Turning to the raw return to the non-credit conferences, the results are puzzling. The raw returns to the non-credit conferences in both treatment and control groups are negatively significant. However, the economic magnitude of the raw return in the treatment group seems smaller than the control group. Panels (E) and (F) of Table 2.3 present the mean and the median of the abnormal return. In Panel (E), the first and the second columns report the mean for credit conferences and non-credit conferences separately. For the credit conferences, the abnormal returns are all positively significant at least at 5% level, ranging from 6.65 bps to 12.27 bps across different measures of abnormal returns, whilst the mean of abnormal return for the non-credit conferences is also significant but the economic magnitude is much smaller than the credit conferences, ranging from 1.19 bps to 2.01 bps. The last column reports the test of the difference of the abnormal return between the two types of the conferences. All results are significant. Panel (F) presents the test of the median of the abnormal return. We use bootstrapped standard errors with 1000 replications. The result is similar to

[59] We cluster the standard error of the raw return in the control group by dates.

the mean test of the abnormal return, albeit with three insignificant results for the credit conference and for the difference tests. In sum, consistent with our expectation, both panels (E) and (F) suggest that the bond market reacts to the broker-hosted conferences, regardless of the type of the conference. However, the market reaction to the credit conference is more pronounced than the non-credit conference.

The value of firms' information to debt investors increases with firms' probability of financial distress (Merton 1974). We expect that the bond market reaction would be greater if the firm (issuer) has a higher likelihood of financial distress (default risk). To test this hypothesis, we partition the sample by bonds' investment/speculative grade cutoff on the conference day as the credit rating is a good summary of firms' financial distress. We use the Standard & Poor credit rating, and define a bond in the investment-grade group if the bond has a rating equal to or above BBB-. Bonds with a credit rating below BBB- are in the speculative grade group. We present the results in Panel (G) of Table 2.3. Among the credit conference (columns 1 and 2), the number of observations in the speculative-grade group is twenty times greater than that the investment-grade group. In contrast, the non-credit conference shows an opposite case where the number of the observations in the speculative-grade group is only a quarter than that in the investment-grade group. This is consistent with the results in Section 3 that financially distressed firms attend more credit conferences than the financially healthy firms. The results show that the bond market only reacts to the conferences (both credit and non-credit) when the bond is in the speculative grades. The market reaction of the investment-grade bonds is insignificant across all the return measures. In particular, among the "*_m1p1*" measure where it contains least noise, the abnormal return measured by using dirty (clean) price is 13.06 (10.94) bps to the credit conference and 6.70 (5.84) bps to the non-credit conference. The difference in the speculative bond abnormal return between the credit and the non-credit conference seems to be large. Then we test such difference in the last column. However, we do not find evidence to support the speculative-grade bonds receiving a stronger market reaction to the credit conference than to the non-credit conference. This may be explained by the investors' great demand for information when the bond is speculatively graded. Information from either type of the conferences is valuable for investors.

The time to maturity of a bond is another important risk factor, in addition to the default risk. We next assess the market reaction to the conferences of bonds with different time-to-maturity. We partition the sample into two classes based on the short or long time-to-maturity of a bond, and expect a greater market reaction to the bonds with short time-to-maturity. The results presented in Panel (H) of Table 2.3 support our expectation. In particular, we find that the abnormal return to the credit conference is only significant when the bonds have short time-to-maturity. In column (1), the abnormal return are all significant, ranging from 8.48 bps to 19.35 bps in the various return measures. In contrast, none of the return measures in the long time to maturity class is statistically significant at any conventional level. Regarding the non-credit conferences, we do not find a similar pattern. In the "*_m1p1*" group, both short and long time-to-maturity classes demonstrate significant results, and the abnormal return of the long time-to-maturity bonds is almost twice as large as the short time-to-maturity bonds. For the "*_m5p5*" and "*_m10p10*" measures, the partition turns the abnormal return insignificant or weakly significant. The last two columns of the panel present the results of the difference test of the abnormal return between the credit conference and the non-credit conference. In the short time-to-maturity class, all the measures of the abnormal return are significant, indicating that credit conferences can elicit stronger market reaction than non-credit conferences when bonds have short time-to-maturity.

Furthermore, we aggregate the overall abnormal return to the firm level. We use a weighted average approach suggested by Bessembinder et al. (2009). The weight is the market value of the bond on the day prior to the conference date. Panel (I) and Panel (J) of Table 2.3 report the results of testing the mean and the median of the firm-level abnormal return respectively. The results are largely consistent with the bond level tests, although one measure of the abnormal return in the median test for the credit conference is insignificant. For example, in Panel (I), the dirty-price abnormal return is 14.49 bps to the credit conference and 2.03 bps to the non-credit conference in the "*_m1p1*" measure. In the last column, the difference test of the market reaction to the credit and the non-credit conferences is positively significant, suggesting that the market reaction is more pronounced to the credit conference than the non-credit conference. The median test in Panel (J) reports the similar results, but with a smaller economic magnitude in the "*_m1p1*" and the "*_m5p5*" measures.

Finally, we report the stock market reaction to the credit and the non-credit conferences. We use CRSP value-weighted index as the benchmark to calculate the stock abnormal return to both conferences. In order to make the bond market return and the stock market return comparable, we only include firms that are in the final sample of the bond market reaction tests when we conduct the stock return sample. Panel (K) of Table 2.3 present the results. The stock market reaction to the non-credit conference is 10.34 bps and positively significant, which is in line with the finding in Green et al. (2014a) and Bushee et al. (2011). In contrast, we do not find that the stock market reacts to the credit conference as the result is insignificant at any conventional level.

In sum, we use abnormal return as the measure of the market reaction to the conferences and find the evidence that the bond market reacts to both credit and non-credit conferences. In addition, the bond market reaction to the credit conference is more pronounced than to the non-credit conference. Next we examine how the market reactions are associated with the two important risk factors of a bond – default risk and the maturity risk. We find that bonds with speculative grades or with short time-to-maturity have significant abnormal return to credit conferences but bonds with investment grades or with long time-to-maturity do not have any significant abnormal returns. Furthermore, when aggregating the abnormal return to the firm level, we continue finding the significant results of the bond market reaction to both conferences. Lastly, we do not find that the stock market reacts to the credit conference.

2.5 Using trading volume as the measure of the bond market reaction

In this section we use daily trading volume of bonds as the measure to investigate the bond market reaction to credit and non-credit conferences (De Franco et al. 2009; De Franco et al. 2014). The abnormal return test in the previous section may bias towards the most liquid bonds as we require the occurrence of at least one transaction before and another one after the conference to calculate the abnormal return. Bonds that do not trade within 20 trading days centered on the conference are discarded. Using trading volume can mitigate the illiquidity concern as we can set the volume to zero when no transaction occurs within a day. We follow the method in De Franco et al. (2009) and use both raw daily volume and abnormal daily volume to measure the market reaction. More specifically, we obtained bonds' trading volume from the enhanced TRACE for the non-financial and non-utility firms that attend at least one credit conference or non-credit conference from 2005 to 2016. After cleaning the enhanced TRACE dataset as in Section 4, we aggregate the intraday trading volume to the daily level, and scale it by the bond's offering amount (obtained from the Mergent FISD) to construct the raw daily volume of the bond. When there is no trade within a given day, we set the volume equal to zero. Next, we aggregate the bond-level volume to the firm-level by taking the average of the raw daily volume of all bonds outstanding within a firm. We denote the firm-level raw volume as $RawVol$, and use it as the first dependent variable in the volume regression. Turning to the abnormal daily volume (*AbnVol*), we take the difference between the firm-level raw daily volume (*RawVol*) and the firm's average daily volume in the previous six months.[60] Then we use either *RawVol* or *AbnVol* to conduct the volume regression analysis in the following model.

$$\begin{aligned} VOLUME_{jt} = CredConf_{jt} &+ NoncConf_{jt} + EarnAnn_{jt} \\ &+ NegEarn_{jt} + AnBuy_{jt} + AnSell_{jt} \\ &+ AnConflicts_{jt} + AnReport_{jt} + RatUp_{jt} \\ &+ RatDown_{jt} + BondSize_{jt} + MVE_{jt} \\ &+ STVolume_{jt} + FE + \varepsilon_{jt} \end{aligned} \tag{2.4}$$

where $VOLUME_{jt}$ is either the raw trading volume (*RawVol*) or the abnormal volume (*AbnVol*) for firm *j* on day *t. CredConf* (*NoncConf*) is a dummy variable, and takes a value of one when firm *j* attends a credit conference (non-credit conference) on day *t* and the next five trading days (*t*+*5*). We control for a set of events that have a bearing on the trading volume documented in the prior literature (De Franco et al. 2009; De Franco et al. 2014; Easton et al. 2009). These events are earnings announcements (EarnAnn), negative earnings when the earnings is announced (*NegEarn*), provision of analysts' earnings forecasts or recommendations (*AnReport*), analysts issuing "buy" recommendations (*AnBuy*), analysts issuing "sell" recommendations (*AnSell*), analysts issuing recommendations that conflicts with each other (*AnConflicts*), upgrades of credit rating (*RatUp*), and downgrades of credit rating (*RatDown*). They are all dummy variables, and take a value of one from *t-1* to *t+5*, where *t* is the event

[60] As we use the trading days rather than the calendar dates to conduct the volume regression, the previous six-month period is from -125 trading days to -3 trading days.

day. In addition, we also include firm-level control variables, including the average offering amounts of all bonds outstanding with a firm in the logarithm form (*BondSize*), the market value of equity in the logarithm form (*MVE*), and the stock daily volume scaled by the total share outstanding (*STVolume*). In addition, we include fixed effects in the different models to control for the time or firm invariant unobservable factors that influence the bond trading volume, including industry effect (or firm fixed effect), credit rating fixed effect, and day fixed effect.[61] We cluster the standard errors by firms and days. All variables are winsorized at 1% and 99% levels.

Table 2.4 presents the trading volume results. Panel (A) reports the sample creation process. We start from the 2,227 firms attending at least one conference (credit or non-credit) and with at least one bond outstanding during the sample period. After applying similar filters as in the abnormal return test, we have 1,102 firm remained.[62] Next, we expand the 1,102 firms into a firm-day panel, and delete the firm-days that are in default.[63] Then we have 2,202,855 firm-day observations in the final sample. Panel (B) shows that the occurrence of conferences is highly infrequent. We only have 0.11% and 1.37% firm-days that have credit and non-credit conferences. Panel (C) reports the statistical description of all variables used in the regression. As the bond market is highly illiquid, the raw daily volume is positively skewed and with a zero median, and the majority (over 75%) of the abnormal volume is negative.[64] Most of the event-related control dummy variables, such as earnings announcement, changes in credit rating are less than 10%, suggesting that these events are not frequent. The mean of analysts' providing a research report is 0.16, which indicates that one firm receive on average one analyst's research report for a week.[65] Panel (D) reports the main results from different specifications. The results are consistent with our expectations. Specifically, in column (i), the coefficients on both credit conferences and non-credit conferences are positively significant. However, the economic magnitude of the credit conferences is greater than that of the non-credit conferences.

[61] The credit rating classification is the same as in Section 3. We combine all the "+" and "–" in Standard & Poor's credit rating with the middle rating, and create seven rating classes: AAA/AA, A, BBB, BB, B, CCC, and CC/C. We drop the defaulted bonds ("D" as in the credit rating)

[62] As we do not need to calculate the accrued interest, we do not exclude bonds that have an abnormal "day count basis" or "interest payment frequency".

[63] For simplicity, all the firm-days in the trading volume analysis refer to firms on the trading days.

[64] We use the daily raw volume minus the mean of the daily volume in the previous six months to calculate the abnormal volume. The mean volume is always non-negative. When there is no trade on the given day, the daily raw volume is zero. Then the abnormal volume is negative.

[65] 1/0.16 report per day = 6.25 days per report

However, when we add control variables and include industry, rating and day fixed effects in column (ii), the non-credit conference coefficient becomes insignificant whilst the credit conference coefficient is still deeply significant. Turning to column (iii) when we control for the firm fixed effect, the coefficient for the credit conference still remains significant, although only at the 10 % level, and again the non-credit conference coefficient is insignificant. As in Section 4, we expect that the market reacts stronger to the credit conference than the non-credit conference. We test the difference of the coefficients between the credit conference and the non-credit conference, and the results are shown in the bottom of the table (Difference P-value). As shown in the table, the p-values are all smaller or equal to 0.05, indicating that the credit conference elicits a greater market reaction than the non-credit conference. In terms of the economic magnitude, the coefficient on the credit conference in column (iii) is 0.024, indicating an increase of 0.14% (6 days × 0.024%) of the bonds' principal is traded on the day and the next five trading days when a firm attends a credit conference. When we use the abnormal volume as the dependent variable in columns (iv) to (vi), the results are similar to the raw trading volume. We still find a positively significant coefficient on the credit conference, but not on the non-credit conference after we include control variables and fixed effects.

In line with the expectation in the abnormal return test in Section 4, we argue that the market reacts more strongly to credit conferences when the bond has a speculative grade of credit rating. In this regard, we add a dummy variable for bonds with speculative grades (*Specu*), and interact it with the conference indicator variables. We expect the interaction terms for the speculative-grade bonds with the credit conference to be positively significant. Then we conduct the regression analysis with the raw trading volume as the dependent variable, and present the results in Panel (E) of Table 2.4.[66] Column (i) is for the interaction with the credit conference only. The coefficient in *Specu* is 0.089 and significant at the 1% level, which suggests that the daily trading volume of bonds with speculative grades is higher than the bonds with investment grades by 0.089% on average on the days without any conferences. The interaction term with the credit conference has a coefficient of 0.14, meaning that speculative-grade bonds receive an incremental trading volume of 0.14% when their issuer attends

[66] We do not control for the credit rating fixed effect here as we include the speculative-grade dummy variable (*Specu*) to the regression. The results are qualitatively unchanged if we include credit rating fixed effect and drop *Specu*.

the credit conference. The overall daily trading volume effect of the credit conference on the speculative-grade bonds is 0.23%, or 1.37% for the six-day period starting from the day when the credit conference takes place. In other words, the market reaction of the speculative-grade bonds to the credit conference is nearly 10 times as large as to the overall bonds' reaction that are documented in Panel (D) of Table 2.4 (0.14%), regardless of credit rating. Turning to the non-credit conferences, we again fail to find any evidence that the bond market reacts to the non-credit conference, regardless of the investment/speculative grades of the bond.

From the trading volume analyses, we conclude that the bond market reacts to credit conferences that a firm attends, especially when the firm has a speculative grade of credit rating. These findings do not apply to non-credit conferences.

2.6 The change in the yield spread on the secondary market

In this section we investigate the change in the cost of debt after a firm attends a credit or non-credit conference. The finance theory suggests information asymmetry increases the cost of capital (Leland and Pyle 1977; Stiglitz and Weiss 1981; Diamond 1985). Conference presentation is a special type of voluntary disclosure (Bushee et al. 2011), which is an alternative mechanism to reduce the information asymmetry between the firm and the investors. Green et al. (2014) find a reduction in the cost of equity after a firm attends a broker-hosted conference. In a similar vein, we argue that the conference attendance may also reduce the cost of debt. We use firms' public bond yield spread on the secondary market as a proxy of cost of debt (Anderson et al. 2003; Anderson et al. 2004; Mansi et al. 2004; Mansi et al. 2011). Specifically, we obtained bonds' yield-to-maturity for each transaction from the enhanced TRACE from 2005 to 2016, and clean and filter the data as in Section 3. In addition, we also exclude bonds with the time-to-maturity more than 30 years. We follow Becker and Ivashina (2015) and create the dataset on the monthly basis by exploiting the median yield of all transactions occurred on the last active trading day within a month. Then we compute the yield spread as the difference between a bond's yield-to-maturity and the Treasure risk-free yield matched by maturity (Campbell and Taksler 2003; Chen et al. 2007; Huang and Huang 2012; Amiraslani et al. 2017). If there is no Treasury yield with the same maturity, we linearly interpolate the risk-free yield for that maturity. Next, we calculate the firm level yield spread as the weighted average yield spread of all bonds outstanding for the same firm with each bond's offering amount as the weight (Derrien et al. 2016). Finally, we calculate the change of the firm-level yield spread as the difference of the yield spread from month *t-3* to month *t+3* (*Ch.YSpread*).[67] We conduct the regression on a monthly basis in the following model:

$$
\begin{aligned}
Ch.YSpread_{jt} \\
&= CredConfM_{jt} + NoncConfM_{jt} + Ch.RatingM_{jt} \\
&+ Ch.BondValueM_{jt} + Ch.NumBondsM_{jt} \\
&+ Ch.MaturityM_{jt} + Ch.RetVolM_{jt} + Ch.TAM_{jt} \\
&+ Ch.LevM_{jt} + Ch.CashM_{jt} + Ch.ROAM_{jt} + FE \\
&+ \varepsilon_{jt}
\end{aligned} \tag{2.5}
$$

where *CredConfM* (*NoncConfM*) is the dummy variable, and equals one if a firm attends at least one credit (non-credit) conference within a month. *Ch.RatingM* is the change in the average credit rating for a firm, where the average credit rating is the average of the numerical Standard & Poor's credit rating for all bonds outstanding for a firm within a month.[68] *Ch.BondvalueM*, *Ch.NumBondsM*, and *Ch.MaturityM* are the changes of a firm's total bond value in the logarithm form, total number of bonds outstanding, and the average time-to-maturity. *Ch.RetVolM* is the change of the bond issuer's market-adjust stock return volatility. All these changes are calculated from the month *t-3* to the month *t+3*.[69] We also control for the changes of firm fundamental variables, including total assets in the logarithm form (*Ch.TAM*), financial leverage (*Ch.LevM*), cash and short-term investment holding scaled by total assets (*Ch.CashM*), and return on total assets in the previous four quarters (*Ch.ROAM*). All the firm fundamental variables are the changes from the previous quarter to the next quarter

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[67] We use the ±3 month change in yield spread as the dependent variable rather than the ±1 month, although the latter contains less noise, because we want to control for the changes in firms' fundamental variables, such as financial leverage. As we cannot obtain the monthly accounting fundamental variables from COMPUSTAT, we use quarterly data instead. Then ±3 month change in yield spread is more appropriate, albeit not perfect, to match with the changes in quarterly fundamental data. In the untabulated analyses where we use ±1 month change in yield spread as the dependent variable, the results are qualitatively unchanged for the regressions either including the changes in firm fundamentals or not.

[68] In line with Baghai et al. (2014), we firstly translate the alphanumeric ratings into a numerical scale by adding one for each rating notch starting from C with the numerical scale of 1, CC with 2, CCC- with 3, etc,, up to a score of 21 for a rating of AAA. We delete the default bonds. Then we calculate the average credit rating of all bonds outstanding for a firm by using the numerical scale, and round it to the integer number.

[69] The market adjusted stock return is defined as the difference between the individual stock return and the CRSP value-weighted return (Campbell and Taksler 2003).

(from *Q-1* to *Q+1*). We also include industry, credit rating, and month-year fixed effects in different models to control for the unobservable factors. All variables are winsorized at 1% and 99% levels.

Panel (A) of Table 2.5 provides the summary statistics. Only 1% and 11% firm-months have at least one credit or non-credit conference as the means of *CredConfM* and *NoncConfM* are 0.01 and 0.11. As the regression is on the "change" basis, the dependent variable *Ch.YSpread* and all explanatory variables, except *Ch.MaturityM*, have a median of zero or close to zero. The median, 25th percentile, and 75th percentile of *Ch.MaturityM* are -6, which is exactly the $\pm$3 month difference. The figure indicates no new bond issue in the most months. Our findings are reported in Panel (B). The first three regressions are conducted in the full sample, whilst the last three are the replicated regressions within the restricted sample where only firms that attend at least one conference over the sample period remain in the sample. We report the valid firm-conference month number within each regression in the middle of the table (NumCredit for the credit conference and NumNonCredit for the non-credit conference). For example, the valid credit conference firm-month in column (iii) is 1,420, which means 1,420 valid credit conference firm-month is used in the regression.[70] The results from the restricted sample and the full sample are very similar, thus we focus on the full sample only. Across all models, the coefficients of firms attending credit conferences are always significant, but the non-credit conference coefficients are only significant in the most parsimonious model. In particular, in column (iii), where we include firm-level control variables, industry, month-year, and credit rating fixed effects, the estimated coefficient on the *CredConfM* is -0.195 and significant at 5% level, but insignificant on the *NoncConfM*. This suggests that a firm experiences on average 19.5 bps reduction in yield spread after attending credit conferences, but the non-credit conference has no bearing on firms' yield spread. The effect of the credit conference is economically large, compared to 44 bps of the mean of the change in yield spread. With respect to control variables, the results are largely consistent with prior literature and intuitions. The

[70] In this section, we do not conduct the investment/speculative grade partition as we do in the trading volume section due to the severe data attrition on the valid credit conference for the investment grade in the final regression. For example, in column (iii), the number of valid credit conference firm-month is 1,420, among which only 35 are for firms with investment grades.

coefficient on the *Ch.RatingM* in column (iii) is -0.626, suggesting that one notch improvement in credit rating is associated with 62.6 bps reduction in the yield spread on average. The positive coefficient on the change in excess stock return volatility (*Ch.RetVolM*) is consistent with the finding in Campbell and Taksler (2003) that idiosyncratic firm-level volatility can explain the cross-sectional variations in the corporate bond yield. In addition, an increase in the financial leverage is related to an increase in the yield spread as suggested by the positive coefficient on *Ch.LevM*.

In this section we conduct the test regarding the change in the cost of debt for a firm attending a conference within a month. We find that firms experience a reduction in the cost of debt, as measured by the bond yield spread on the secondary market, after a credit conference. However, we do not find such reduction in the following months after the non-credit conference.

2.7 Bond institutional investor ownership

In this section we investigate the change in the bond institutional investor ownership after a firm attends credit conferences. We hypothesize that conferences, as an alternative information disclosure mechanism, are associated with the increase in the institutional ownership. Green et al. (2014) and Bushee et al. (2011) document an increase in equity institutional investors after a firm attends a broker-hosted conference. We focus on the institutional ownership of bonds with non-financial and non-utility issuers in this paper. We firstly test the overall change of bonds' ownership, then we test how the mutual fund investor and the insurance company, the two major owners respond to the credit conference and the non-credit conference. We obtained the bond ownership data from the Lipper eMAXX. This dataset contains quarter-end issue level holding for the major institutional investors including mutual funds, insurance companies, and pension funds. We define the bond institutional investor ownership as the total amount of bond held by all institutional investors recorded in the Lipper eMAXX within each quarter, scaled by the offering amount of the bond. Then we conduct our analysis on the bond-quarter level.[71] Next, we test the change in the bond ownership of the two major investors, mutual funds and insurance companies separately as these two are subject to different level of regulatory constraints, which

[71] Lipper eMAXX provides not only corporate bond ownership, but also municipal bond ownership, as well as the public and the private issues. To ensure the homogeneity of the sample, we only use the bond ownership data whose issuer *cusip* (first 6 digits) can be found in Compustat.

may affect their trading behavior. We use the managing firm classification provided in eMAXX to classify the types of investors (Dass and Massa 2014; Manconi et al. 2016).[72] Specifically, we categorize the institutional investors into five major groups: mutual funds, insurance companies, pension funds, banks, and brokerage houses.[73] The mutual fund group and the insurance company group account for nearly 90% among all the institutional investor ownership. We define the dependent variable, the change in the institutional investor ownership (*Ch.INST*), as the difference of the bond institutional ownership from the quarter *t-1* to the quarter *t+1*. The regression is as follows:

$$\begin{aligned} Ch.Inst_{ijt} = {} & CredConfQ_{jt} + NoncConfQ_{jt} + Ch.RatingQ_{ijt} \\ & + Ch.NumTradeQ_{ijt} + Ch.VolTradeQ_{ijt} \\ & + Ch.RetVolQ_{jt} + Ch.MVEQ_{jt} + Ch.LevQ_{jt} \\ & + Ch.CashQ_{jt} + FE + \varepsilon_{ijt} \end{aligned} \tag{2.6}$$

where (*Ch.Inst*) is the change in the bond institutional investor for bond *i* with the issuer *j* at quarter *t*, which contains three types: the overall investor (*Ch.InstALL*), the mutual fund investor (*Ch.InstMUT*), and the insurance company investor (*Ch.InstINS*). *CredConfQ* (*NoncConfQ*) is the dummy variable with the value of one when the firm attends at least one credit conference (non-credit conference) within the quarter. *Ch.RatingQ*, *Ch.NumTradeQ*, and *Ch.VolTradeQ* are the bond related variables, which are the change in credit rating, the change in the number of trades in the logarithm form, and the change in the trading volume scaled by the offering amount. We also control for the change of firm-level variables, including the change in the excess return volatility (*Ch.RetVolQ*), the change in the market value of equity (*Ch.MVEQ*), the change in financial leverage (*Ch.LevQ*), and the change in cash and short-term investment holding scaled by total assets (*Ch.CashQ*). All variables are the change

[72] Lipper eMAXX provides the classification at both the fund level and the managing firm level. We follow Dass and Massa (2014) and use the managing firm level classification code.

[73] The corresponding Lipper eMAXX codes to these five groups are: MUT and INM for mutual funds; ILF, IMD, IND, IPC, and REI for insurance companies; CPE, GPE, and UPE for pension funds, BKG, BKM, BKP, BKT, CRU, SVG, TRT for banks; as well as BFM and BMS for the brokerage houses. The remaining codes are classified into the others. In Dass and Massa (2014), they only classify the investor with the firm code of MUT as the mutual fund investor. We add INM to the mutual fund group for two reasons. Firstly, the INM holding proportion is significantly large (If we classify the INM into the other group, the mutual fund group would reduce to less than 1%). Second, we check the corresponding fund-level codes and find that over 40% of mutual fund (fund level) codes belong to the INM group at the firm level.

variables from the quarter *t-1* to quarter *t+1*. Additionally, we control for firm, year, credit rating, and time-to-maturity fixed effects (*FE*) in different specifications.

Panel (A) of Table 2.6 reports the data statistics. As the variables in the regression are the changes between two quarters, most of the variables have a median of zero, or close to zero. The means of *CredConfQ* and *NoncConfQ* are 0.05 and 0.53 respectively, indicating that 5% and 53% bond-quarters in the sample have credit conferences and non-credit conferences. Panel (B) presents the main results in the different specifications and with different dependent variables. Columns (i) to (iii) are the regressions with the dependent variable of overall bond institutional investor ownership, regardless of the type. After we control for the firm, year, credit rating, and time-to-maturity fixed effect in regression (ii), we find a positively significant coefficient on the credit conference quarter, suggesting an increase in the bond institutional investor ownership after the issuer attends a credit conference. In contrast, the coefficient on the non-credit conference is insignificant, which indicates that firms attending a non-credit conference have little impact on the bond institutional investors. Mutual funds and insurance companies are the major bond institutional investors and have different investment strategies due to the regulatory constraints. Regulation requires insurance companies to maintain a minimum level of capital on a risk-adjusted basis so that such capital increases with the bond's credit risk. Therefore, insurance companies mainly invest in investment-grade bonds, and may force to sell the bonds that are downgraded (Becker and Ivashina 2015; Ellul et al. 2011). In the section 3, we find that one of the major determinants of a firm attending credit conferences is the probability of financial distress. In addition, Section 4 shows that the majority of bonds in the credit conference are in the speculative grades. Thus we argue that the insurance company investors may not react to the credit conference where the speculative-grade bonds dominate. The increase in the overall bond institutional investor ownership we documented in the columns (ii) to (iii) may be attributed to the mutual fund investors mainly. We then test the ownership of mutual fund investors and insurance companies react to conferences separately. Columns (iv) to (vi) report the regression results with the mutual fund ownership as the dependent variable, whilst columns (vii) to (ix) are for the insurance company ownership. Within the mutual fund set, we continue to find the significant results for the credit conference but not for the non-credit conference. In contrast, in the insurance company ownership group (columns vii to ix), the results do not hold anymore, as the *CreditConfQ* coefficient is not significant at any conventional level when we include control variables and various fixed effects. Therefore, we find evidence consistent with our expectation that the bond institutional investor ownership increases with the credit conference attendance, and this increase is mainly ascribed to the mutual fund investors. Next, we partition the sample by the bonds credit rating (speculative grades versus investment grades) and re-run the regression (2.6). Panel (C) of Table 2.6 suggests that the majority of the sample is in the investment grades as the observations of the bond-quarters within the investment-grade subsample (iv to vi) are more than twice as in the speculative-grade subsample (i to iii). The coefficients of the credit conference on the changes in the overall ownership and in the mutual fund ownership are only significant in the speculative-grade subsample, not in the investment-grade subsample. This is consistent with the results from the market reaction tests that only speculative-grade bonds could elicit market reactions to the credit conference.

2.8 Conclusion

In this paper, we investigate the effects of the broker-hosted conferences on the corporate bond market. We identify a subset of conferences that are organized with the credit investors oriented. Then we study how the corporate bond market reacts to credit conferences, as well as to the non-credit conferences. We firstly investigate the determinants of firms attending credit conferences, and we find that firms with greater financial distress, more public bonds outstanding, and greater intention of debt refinancing have a higher likelihood of attending credit conferences. We do not find a similar pattern for non-credit conferences. Next, we use both abnormal return and trading volume to examine the bond market reaction to both conferences. We find that the market mainly reacts to credit conferences. Although we do find significant abnormal returns to non-credit conferences, the economic magnitude is very small, relative to credit conferences. In the cross-sectional test, we further find a greater market reaction to the credit conference when the bonds have speculative grades and short time-to-maturity. Furthermore, we find that firms attending credit conferences experience a reduction in the cost of debt as measured by the change in the yield spread on the secondary market. Lastly, we document a significant increase in the bond institutional ownership in the following quarter after firms participate in credit conferences, and such increase is mainly attributed to the mutual fund ownership and when the bond has a speculative grade of the credit rating. But neither the reduction in cost of debt nor the increase in bond institutional investor ownership apply to non-credit conferences.

2.9 Appendix: Definition of variables

Bond return variables		
Variable Name	Description	Source
RET_D_m1p1	Raw return of a bond around a conference, calculated by using the bond dirty price one day before the conference and one day after the conference. If there is no transaction on these two days, the observation is discarded.	Mergent FISD, enhanced TRACE
RET_C_m1p1	Raw return of a bond around a conference, calculated by using the bond clean price one day before the conference and one day after the conference. If there is no transaction on these two days, the observation is discarded.	Mergent FISD, enhanced TRACE
RET_D_m5p5	Raw return of a bond around a conference, calculated by using the bond dirty price one day before the conference and one day after the conference. If there is no transaction on these two days, the before-conference price is replaced with the last price within the five trading days before the conference; and the after-conference price is replaced with the first price within the five trading days after the conference. If still no applicable price, the observation is discarded.	Mergent FISD, enhanced TRACE
RET_C_m5p5	Raw return of a bond around a conference, calculated by using the bond clean price one day before the conference and one day after the conference. If there is no transaction on these two days, the before-conference price is replaced with the last price within the five trading days before the conference; and the after-conference price is replaced with the first price within the five trading day after the conference. If still no applicable price, the observation is discarded.	Mergent FISD, enhanced TRACE
RET_D_m10p10	Raw return of a bond around a conference, calculated by using the bond dirty price one day before the conference and one day after the conference. If there is no transaction on these two days, the before-conference price is replaced with the last price within the ten trading days before the conference; and the after-conference price is replaced with the first price within the five trading days after the conference. If still no applicable price, the observation is discarded.	Mergent FISD, enhanced TRACE

RET_C_m10p10	Raw return of a bond around a conference, calculated by using the bond clean price one day before the conference and one day after the conference. If there is no transaction on these two days, the before-conference price is replaced with the last price within the ten trading days before the conference; and the after-conference price is replaced with the first price within the five trading days after the conference. If still no applicable price, the observation is discarded.	Mergent FISD, enhanced TRACE
ABRET_D_m1p1	Abnormal return of a bond, calculated by taking the difference of the ***RET_D_m1p1*s** between the treatment group (the issuer attending a conference on the day) and the control group (the aggregated return of the whole universe of the Mergent FISD whose issuers do not attend any conference on the day).	Mergent FISD, enhanced TRACE
ABRET_C_m1p1	Abnormal return of a bond, calculated by taking the difference of the ***RET_C_m1p1*s** between the treatment group (the issuer attending a conference on the day) and the control group (the aggregated return of the whole universe of the Mergent FISD whose issuers do not attend any conference on the day).	Mergent FISD, enhanced TRACE
ABRET_D_m5p5	Abnormal return of a bond, calculated by taking the difference of the ***RET_D_m5p5*s** between the treatment group (the issuer attending a conference on the day) and the control group (the aggregated return of the whole universe of the Mergent FISD whose issuers do not attend any conference on the day).	Mergent FISD, enhanced TRACE
ABRET_C_m5p5	Abnormal return of a bond, calculated by taking the difference of the ***RET_D_m5p5*s** between the treatment group (the issuer attending a conference on the day) and the control group (the aggregated return of the whole universe of the Mergent FISD whose issuers do not attend any conference on the day).	Mergent FISD, enhanced TRACE
ABRET_D_m10p10	Abnormal return of a bond, calculated by taking the difference of the ***RET_D_m10p10*s** between the treatment group (the issuer attending a conference on the day) and the control group (the aggregated return of the whole universe of the Mergent FISD whose issuers do not attend any conference on the day).	Mergent FISD, enhanced TRACE
ABRET_C_m10p10	Abnormal return of a bond, calculated by taking the difference of the ***RET_C_m10p10*s** between the treatment group (the issuer attending a conference on the day) and the control group (the aggregated return of the whole universe of the Mergent FISD whose issuers do not attend any conference on the day).	Mergent FISD, enhanced TRACE

Variables used in the determinant regressions		
Variable Name	Description	Source
AF	Analysts follow.	I/B/E/S
CASH	Cash holding scaled by total assets.	
CONF	Categorical variable, with the value of zero if the firm does not attend any conference within a year, with the value of one if the firm only attends non-credit conferences within a year; with the value of two if the firm only attends credit conference within a year; and with the value of three if the firm attends both credit conference and non-credit conference.	COMPUSTAT
DISTA_DEFT	Numerical distance to default, provided by the Risk Management Institute at the National University of Singapore.	Risk Management Institute at NUS
INSTBD_INS	The amount of bonds held by insurance companies divided by the offering amount, aggregated to the firm level.	Lipper eMAXX
INSTBD_MUT	The amount of bonds held by mutual funds divided by the offering amount, aggregated to the firm level.	Lipper eMAXX
INSTEQ	The percentage of equity institutional ownership.	Thomson Reuters
INTA	Intangible assets scaled by total assets.	COMPUSTAT
JUSTBELOW	Dummy variable with the value of one if the S&P credit rating is BBB or BBB-, and zero otherwise.	COMPUSTAT
LEV	Financial leverage, defined as total liabilities scaled by total assets.	COMPUSTAT
MAT	The average time to maturity of all bonds outstanding.	Mergent FISD
MB	Market value of equity divided by book value of equity.	COMPUSTAT
MVE	Market value of equity in the logarithm form.	COMPUSTAT
NOBOND	Dummy variable, with the value of one if the firm has no bond outstanding within a year, and zero otherwise.	COMPUSTAT
NUMBD	The number of bonds outstanding within a firm.	Mergent FISD
NUMEQ	The number of equity institutional investors.	Thomson Reuters
OABD	The total offering amount of bonds outstanding in the logarithm form.	Mergent FISD
RETVOL	The standard deviation of a firm’s market adjusted stock return. Market adjusted stock return is the difference between the individual stock return and the CRSP Value-weighted return.	COMPUSTAT
ZSCORE	Altman's Z-score.	COMPUSTAT

Variables used in the trading volume regressions		
Variable Name	Description	Source
AbnVol	Abnormal trading volume, defined by the raw daily trading volume minus the mean of the trading volume of the bond in the previous half a year, then aggregated to the firm level.	Enhanced TRACE
AnBuy	Dummy variable, with the value of one if an analyst provides a "Buy" recommendation on the day for a firm, and zero otherwise.	I/B/E/S
AnConflicts	Dummy variable, with the value of one if different analysts provides conflict opinions on the same day for the same firm, and zero otherwise.	I/B/E/S
AnReport	Dummy variable, with the value of one if an analyst provides any forecasts or recommendations on the day for a firm, and zero otherwise.	I/B/E/S
AnSell	Dummy variable, with the value of one if an analyst provides a "Sell" recommendation on the day for a firm, and zero otherwise	I/B/E/S
BondSize	The average offering amount of all bonds outstanding in the logarithm form.	Mergent FISD
CredConf	Dummy variable, with the value of one if the firm (issuer) attends a credit conference on the day, and zero otherwise.	Bloomberg
EarnAnn	Dummy variable, with the value of one if the firm announces the earnings on the day, and zero otherwise.	I/B/E/S
MVE	Market value of equity in the logarithm form, defined as the total shares outstanding times the stock price.	COMPUSTAT
NegEarn	Dummy variable, with the value of one if the firm announces negative earnings on the day, and zero otherwise.	I/B/E/S
NoncConf	Dummy variable, with the value of one if the firm (issuer) attends a non-credit conference on the day, and zero otherwise.	Bloomberg
RatDown	Dummy variable, with the value of one if the credit rating of any bonds of a firm is downgraded, and zero otherwise.	Mergent FISD
RatUp	Dummy variable, with the value of one if the credit rating of any bonds a firm is upgraded, and zero otherwise.	Mergent FISD
RawVol	The raw daily trading volume, defined as the total trading volume of a bond scaled by its offering amount, then aggregated to the firm level.	Enhanced TRACE
Specu	Dummy variable, with the value of one if the firm's average credit rating is in the speculative grades.	Mergent FISD
STVolume	The daily stock volume scaled by the total common stock outstanding.	CRSP

Variables used in the cost of debt regressions		
Variable Name	Description	Source
Ch.BondValueM	Changes in the total bond offering amount in the logarithm form from the previous three months to the next three months.	Mergent FISD
Ch.CashM	Changes in the cash and short-term holding scaled by total assets from the previous three months to the next three months.	COMPUSTAT
Ch.LevM	Changes in financial leverage from the previous three months to the next three months. Financial leverage is defined as total liabilities scaled by total assets.	COMPUSTAT
Ch.MaturityM	Changes in the average time to maturity of all the bonds from the previous three months to the next three months.	Mergent FISD
Ch.NumBondsM	Changes in the total number of bond outstanding in the logarithm form from the previous three months to the next three months.	Mergent FISD
Ch.RatingM	Changes in the average credit rating of a firm from the previous three months to the next three months.	Mergent FISD
Ch.RetVolM	Changes in the market adjusted return volatility of a firm from the previous three months to the next three months. Market adjusted return volatility is the difference between the individual stock return and the CRSP value-weighted return.	CRSP
Ch.ROAM	Changes in the return on assets in preceding four quarters from the previous three months to the next three months.	COMPUSTAT
Ch.TAM	Changes in the total assets in the logarithm form from the previous three months to the next three months.	COMPUSTAT
Ch.YSpread	Changes in the average yield spread of all bonds for a firm from the previous three months to the next three months.	Enhanced TRACE
CreditConfM	Dummy variable, with the value of one if the firm attends a credit conference within a month, and zero otherwise.	Bloomberg
NoncConfM	Dummy variable, with the value of one if the firm attends a non-credit conference within a month, and zero otherwise.	Bloomberg

Variables used in the bond ownership regressions		
Variable Name	Description	Source
Ch.CashQ	Change in the cash and short-term investment scaled by total assets from the previous quarter to the next quarter.	COMPUSTAT
Ch.InstALL	Change in the total bond institutional investor ownership from the previous quarter to the next quarter.	Lipper eMAXX
Ch.InstINS	Change in the insurance company ownership from the previous quarter to the next quarter.	Lipper eMAXX
Ch.InstMUT	Change in the mutual fund ownership from the previous quarter to the next quarter.	Lipper eMAXX
Ch.LevQ	Change in the financial leverage from the previous quarter to the next quarter.	COMPUSTAT
Ch.MVEQ	Change in the market value of equity from the previous quarter to the next quarter.	COMPUSTAT
Ch.NumTradeQ	Change in the total number of trades of a bond in the logarithm form from the previous quarter to the next quarter.	Enhanced TRACE
Ch.RatingQ	Change in the credit rating of a bond from the previous quarter to the next quarter.	Mergent FISD
Ch.RetVolQ	Change in the market adjusted stock return of the issuer from the previous quarter to the next quarter. Market adjusted return volatility is the difference between the individual stock return and the CRSP value-weighted return.	CRSP
Ch.VolTradeQ	Change in the total trading volume of a bond, scaled by the offering amount from the previous quarter to the next quarter.	Enhanced TRACE
CreditConfQ	Dummy variable, with the value of one if the firm attends a credit conference within a quarter, and zero otherwise.	Bloomberg
NoncConfQ	Dummy variable, with the value of one if the firm attends a non-credit conference within a quarter, and zero otherwise.	Bloomberg

Table 2.1: Data collection

This table reports the general description of the conference data. Panel (A) presents the data collection process. Panel (B) reports the conference attendance within a year. Panel (C) presents conferences hosted by the major brokerage houses.

Panel (A): Conference data collecting process

Sample period: 2005-2016		Observations
Raw data scraped from Bloomberg (firm-conference observations)		237,528
less non-broker-hosted, or unidentifying brokers or firms	*77,344*	
Firm-conference		160,184
Of which credit conference	4,380	
Of which non-credit conference	155,804	

Number of unique companies	7,144
Companies that have bonds outstanding during the sample period	**2,227**
Number of bonds outstanding during the sample period	**17,935**

Panel (B): Conference attendance by year

	Credit conferences				Non-credit conferences			
Year	Firm-conference	Unique conferences	Unique brokers	Firm-year	Firm-conference	Unique conference	Unique brokers	Firm-year
2005	273	15	8	170	12,218	466	109	3,153
2006	300	10	8	200	13,027	538	120	3,241
2007	218	10	9	138	13,279	604	124	3,308
2008	219	7	7	138	12,875	621	127	3,233
2009	314	14	9	212	11,527	570	118	2,911
2010	447	14	10	264	14,742	655	121	3,234
2011	519	18	10	295	15,084	656	118	3,222
2012	577	14	7	354	13,696	614	120	3,115
2013	473	12	7	308	12,526	602	116	2,952
2014	433	11	9	288	12,801	596	109	3,064
2015	353	12	8	242	12,322	627	110	3,045
2016	254	13	10	160	11,707	630	112	2,951
Total	4,380	150	102	2,769	155,804	7179	1404	37,429
Average	365.0	12.5	8.5	230.8	12,983.7	598.3	117.0	3,119.1

Panel (C): Conferences hosted by major brokerage houses

Name of broker	Credit conferences: Firm-conferences	Credit conferences: Unique conferences	Credit conferences: Ave. No. of firm per conf.	Non-credit conferences: Firm-conferences	Non-credit conferences: Unique conferences	Non-credit conferences: Ave. No. of firm per conf.
Deutsche Bank	1,015	15	67.7	5,676	239	23.7
J. P. Morgan	896	14	64.0	7,279	248	29.4
Bank of America Merrill Lynch	791	19	41.6	4,869	254	19.2
Barclays	434	16	27.1	4,693	195	24.1
Credit Suisse	262	13	20.2	6,436	398	16.2
Lehman Brothers	190	7	27.1	2,399	62	38.7
Bank of America	154	5	30.8	2,403	72	33.4
Citigroup	139	8	17.4	5,928	239	24.8
Bear Stearns	133	4	33.3	1,760	51	34.5
UBS	123	3	41.0	5,940	368	16.1
Goldman Sachs	116	22	5.3	5,433	304	17.9
Morgan Stanley	52	3	17.3	4,604	247	18.6
Merrill Lynch	21	2	10.5	1,919	121	15.9
Royal Bank of Scotland	20	3	6.7	-	-	-
Wachovia	12	1	12.0	1,145	34	33.7
Others	22	15	1.5	95,320	4,347	21.9
Total	4,380	150	29.2	155,804	7,179	21.7
Total number of brokers:		24			246	

Table 2.2: Determinants of firms attending credit and non-credit conferences

This table reports the data description and the test results of the determinants of firms attending credit and non-credit conferences. We use a multinomial logit model with the dependent variable of *CONF*. *CONF* takes value of zero if a firm does not attend any conference within a year, value of one if a firm attends the non-credit conference only within a year, value of two if a firm attends the credit conference only within a year, and value of three if a firms attend both non-credit and credit conference within a year. Panel (A) reports the process of the sample creation, for both full sample and restricted sample where firms with no bond outstanding are excluded. Panels (B) and (C) present descriptive statistics and outline the results for the full sample respectively. Panels (D) and (E) present descriptive statistics and outline the results for the restricted sample respectively. Variables are cash ratio (*CASH*), Altman Z-score (*ZSCORE*), financial leverage (*LEV*), market adjusted stock return volatility (*RETVOL*), distance to default (*DISTA_DEFT*), the dummy variable of just below investment grade cutoff ($JUSTBELOW$), and the equity institutional investor holding percentage (*INSTEQ*) and the number (*NUMEQ*); and the number, value, and average time to maturity of firms' bond outstanding (*NUMBD*, *MVBD*, *MAT*), and bonds' insurance company ownership and mutual fund ownership (*INSTBD_INS*, *INSTBD_MUT*); and the market value of equity in the logarithm form (*MVE*), intangible assets scaled by total assets (*INTA*), market-to-book ratio (*MB*), and equity analyst following (*AF*), as well as a dummy variable for firms with no bond outstanding (*NOBOND*). All variables are one year lagged (except *NOBOND*). Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Sample creation

	i		ii		iii		iv		v	
CONF	Firm-year	%	Firm-year	%	Firm-year	%	Firm-year	%	Firm-year	%
1	35,140	92.7%	30,277	44.3%	23,991	44.8%	17,526	67.6%	6,290	75.2%
2	480	1.3%	205	0.3%	191	0.4%	106	0.4%	78	0.9%
3	2,289	6.0%	2,020	3.0%	1,827	3.4%	1,224	4.7%	967	11.6%
0	-	-	35,823	52.4%	27,487	51.4%	7,052	27.2%	1,032	12.3%
Total	37,909		68,325		53,496		25,908		8,367	

i	Conference attending firm-year observations from Bloomberg.
ii	Total firm-year observations on Compustat from 2005 to 2016.
iii	Compustat from 2005 to 2016 after deleting financial and utility industries.
iv	Final sample where all one-year lagged variables are not missing.
v	Final sample excluding "no-bond" firms.

Panel (B): Data description for the final sample where all one-year lagged variables are not missing

	CONF=1			CONF=2			CONF=3			CONF=0		
Variable	Mean	S.D.	Median	Mean	S.D.	Median	Mean	S.D.	Median	Mean	S.D.	Median
LEV	0.53	0.32	0.49	0.88	0.35	0.82	0.83	0.32	0.77	0.49	0.31	0.44
ZSCORE	4.83	6.88	3.65	1.59	1.35	1.35	1.76	1.50	1.66	4.16	6.58	3.48
DISTA_DEFT	5.26	2.67	4.83	3.10	1.62	3.00	3.58	1.97	3.38	4.40	2.72	3.85
CASH	0.28	0.31	0.17	0.09	0.10	0.06	0.09	0.13	0.06	0.19	0.22	0.12
NOBOND	0.64	0.48	1.00	0.26	0.44	0.00	0.21	0.41	0.00	0.85	0.35	1.00
NUMBD	1.68	3.40	0.00	3.88	4.60	2.00	4.19	4.35	3.00	0.57	1.89	0.00
OABD	4.72	6.57	0.00	9.90	6.32	13.10	10.66	5.99	13.51	1.90	4.66	0.00
MAT	2.93	5.17	0.00	3.98	3.15	4.73	4.77	3.96	4.79	0.98	3.08	0.00
JUSTBELOW	0.06	0.23	0.00	0.15	0.36	0.00	0.25	0.44	0.00	0.03	0.17	0.00
INTA	0.23	0.25	0.15	0.26	0.27	0.19	0.29	0.30	0.21	0.14	0.20	0.06
RETVOL	0.03	0.01	0.02	0.03	0.01	0.02	0.03	0.01	0.02	0.03	0.02	0.03
MVE	6.83	1.85	6.72	6.68	1.46	6.71	7.25	1.30	7.29	5.08	1.93	4.87
MB	3.38	4.99	2.43	2.04	7.55	1.47	2.35	6.32	1.90	2.32	3.94	1.64
AF	10.91	9.33	8.00	6.68	6.15	5.00	11.93	8.87	10.00	3.60	6.31	1.00
INSTEQ	0.63	0.29	0.72	0.60	0.31	0.70	0.68	0.28	0.76	0.38	0.31	0.33
NUMEQ	4.46	1.58	4.76	4.16	1.62	4.62	4.60	1.50	4.96	3.24	1.64	3.40
INSTBD_MUT	0.05	0.10	0.00	0.10	0.12	0.08	0.14	0.13	0.13	0.02	0.06	0.00
INSTBD_INS	0.04	0.10	0.00	0.03	0.05	0.01	0.04	0.05	0.01	0.01	0.06	0.00
Observations		17,526			106			1,224			7,052	

Panel (C): Regression results

	Benchmark: CONF=0			Benchmark: CONF=1	
Dep.Var=	CONF=1	CONF=2	CONF=3	CONF=2	CONF=3
	i	ii	iii	iv	v
LEV	-0.313***	1.238***	1.056***	1.551***	1.369***
	(0.103)	(0.324)	(0.195)	(0.319)	(0.179)
ZSCORE	-0.009*	-0.059*	-0.063***	-0.049	-0.054***
	(0.005)	(0.035)	(0.017)	(0.035)	(0.016)
DISTA_DEFT	-0.116***	-0.594***	-0.426***	-0.478***	-0.310***
	(0.017)	(0.095)	(0.038)	(0.094)	(0.035)
CASH	1.283***	-2.746**	-2.115***	-4.029***	-3.398***
	(0.145)	(1.186)	(0.566)	(1.183)	(0.553)
NOBOND	-0.483***	-1.106**	-1.530***	-0.623	-1.048***
	(0.152)	(0.479)	(0.224)	(0.469)	(0.194)
NUMBD	-0.025	0.044	0.029	0.069	0.053***
	(0.023)	(0.060)	(0.029)	(0.059)	(0.020)
OABD	-0.038**	0.056	0.016	0.094**	0.054***
	(0.015)	(0.043)	(0.021)	(0.042)	(0.017)
MAT	0.020	-0.085***	-0.054***	-0.105***	-0.074***
	(0.013)	(0.031)	(0.019)	(0.030)	(0.016)
JUSTBELOW	-0.165	0.309	0.743***	0.474	0.908***
	(0.148)	(0.355)	(0.194)	(0.334)	(0.136)
INTA	1.270***	1.260***	1.648***	-0.010	0.378
	(0.165)	(0.467)	(0.293)	(0.455)	(0.254)
RETVOL	-0.618	-1.598	-5.015	-0.979	-4.397
	(2.100)	(9.710)	(4.548)	(9.685)	(4.318)
MVE	0.409***	0.827***	0.642***	0.417***	0.232***
	(0.037)	(0.141)	(0.069)	(0.141)	(0.059)
MB	0.016***	0.005	0.008	-0.010	-0.008
	(0.006)	(0.022)	(0.009)	(0.022)	(0.008)
AF	0.062***	-0.061**	0.032**	-0.124***	-0.031***
	(0.011)	(0.030)	(0.014)	(0.029)	(0.009)
INSTEQ	1.681***	1.411*	2.275***	-0.270	0.594*
	(0.194)	(0.761)	(0.358)	(0.751)	(0.310)
NUMEQ	-0.526***	-0.015	-0.661***	0.511	-0.136
	(0.087)	(0.457)	(0.204)	(0.455)	(0.192)
INSTBD_MUT	-0.072	1.528	1.816**	1.600	1.888***
	(0.589)	(1.751)	(0.766)	(1.670)	(0.563)
INSTBD_INS	0.019	-6.664***	-8.343***	-6.683***	-8.362***
	(0.559)	(2.149)	(1.095)	(2.102)	(0.970)
Constant	-1.926***	-6.530***	-5.882***	-4.604***	-3.956***
	(0.650)	(1.588)	(0.952)	(1.575)	(0.805)
Observations		25,908		25,908	
Pseudo R2		0.291		0.291	
Industry FE		Yes		Yes	
Year FE		Yes		Yes	

Panel (D): Final sample excluding "no-bond" firms

	CONF=1			CONF=2			CONF=3			CONF=0		
Variable	Mean	S.D.	Median	Mean	S.D.	Median	Mean	S.D.	Median	Mean	S.D.	Median
LEV	0.65	0.30	0.61	0.87	0.35	0.76	0.83	0.32	0.77	0.68	0.30	0.63
ZSCORE	3.34	3.66	3.00	1.54	1.32	1.39	1.69	1.32	1.65	3.12	3.67	2.83
DISTA_DEFT	5.70	2.90	5.23	3.20	1.60	3.07	3.58	1.95	3.39	4.94	2.93	4.41
CASH	0.19	0.24	0.11	0.08	0.10	0.06	0.09	0.11	0.06	0.14	0.18	0.08
NUMBD	4.67	4.28	3.00	5.27	4.63	4.00	5.29	4.26	4.00	3.83	3.46	2.00
OABD	12.96	3.47	13.59	13.46	2.46	13.83	13.41	2.87	13.83	12.61	3.17	13.23
MAT	8.19	5.60	7.00	5.41	2.38	5.17	6.04	3.49	5.71	6.70	5.16	5.00
JUSTBELOW	0.12	0.32	0.00	0.19	0.40	0.00	0.27	0.45	0.00	0.12	0.33	0.00
INTA	0.27	0.25	0.21	0.27	0.26	0.20	0.27	0.29	0.18	0.20	0.23	0.12
RETVOL	0.02	0.01	0.02	0.03	0.01	0.02	0.03	0.01	0.02	0.02	0.02	0.02
MVE	8.10	1.69	8.06	6.78	1.47	6.74	7.32	1.30	7.33	7.09	1.84	6.88
MB	3.43	5.55	2.48	2.23	8.20	1.49	2.46	5.84	1.90	2.93	5.65	1.87
AF	16.18	9.92	15.00	7.10	6.13	6.00	12.87	9.00	11.00	9.26	9.21	6.00
INSTEQ	0.74	0.22	0.78	0.64	0.28	0.71	0.71	0.25	0.77	0.65	0.28	0.71
NUMEQ	5.26	1.32	5.40	4.45	1.35	4.68	4.82	1.23	5.03	4.63	1.47	4.87
INSTBD_MUT	0.14	0.12	0.14	0.14	0.12	0.11	0.17	0.12	0.17	0.12	0.11	0.10
INSTBD_INS	0.12	0.14	0.05	0.04	0.06	0.03	0.04	0.05	0.03	0.10	0.13	0.03
Observations		6,290			78			967			1,032	

Panel (E): Regression results within the sample where "no-bond" firms are excluded

	Benchmark: CONF=0			Benchmark: CONF=1	
Dep.Var=	CONF=1	CONF=2	CONF=3	CONF=2	CONF=3
	i	ii	iii	iv	v
LEV	-0.600***	0.716	0.947***	1.315***	1.547***
	(0.214)	(0.467)	(0.266)	(0.440)	(0.200)
ZSCORE	-0.059***	-0.088	-0.127***	-0.029	-0.068***
	(0.018)	(0.065)	(0.031)	(0.063)	(0.026)
DISTA_DEFT	-0.015	-0.388***	-0.274***	-0.374***	-0.259***
	(0.035)	(0.115)	(0.050)	(0.113)	(0.038)
CASH	1.552***	-3.282**	-3.258***	-4.835***	-4.810***
	(0.379)	(1.551)	(0.669)	(1.527)	(0.596)
NUMBD	-0.002	0.063	0.055*	0.066	0.057***
	(0.025)	(0.062)	(0.030)	(0.061)	(0.021)
OABD	-0.060***	0.098	0.002	0.157	0.062***
	(0.018)	(0.097)	(0.026)	(0.097)	(0.021)
MAT	0.033***	-0.078**	-0.042**	-0.111***	-0.076***
	(0.013)	(0.032)	(0.019)	(0.030)	(0.016)
JUSTBELOW	-0.019	0.644*	0.874***	0.663*	0.893***
	(0.172)	(0.382)	(0.216)	(0.358)	(0.140)
INTA	1.557***	1.327**	1.111**	-0.230	-0.446
	(0.395)	(0.561)	(0.456)	(0.486)	(0.271)
RETVOL	12.263*	12.872	7.573	0.610	-4.690
	(6.981)	(14.313)	(8.049)	(12.788)	(5.155)
MVE	0.275***	0.445**	0.311***	0.170	0.035
	(0.084)	(0.201)	(0.113)	(0.199)	(0.082)
MB	0.003	0.005	0.005	0.002	0.002
	(0.009)	(0.025)	(0.010)	(0.025)	(0.008)
AF	0.071***	-0.073**	0.054***	-0.145***	-0.017*
	(0.013)	(0.033)	(0.016)	(0.031)	(0.009)
INSTEQ	1.568***	0.713	1.842***	-0.856	0.273
	(0.427)	(1.027)	(0.546)	(0.969)	(0.391)
NUMEQ	-0.265***	0.147	-0.225**	0.412**	0.041
	(0.082)	(0.198)	(0.108)	(0.190)	(0.083)
INSTBD_MUT	0.182	2.128	2.832***	1.947	2.650***
	(0.602)	(1.914)	(0.804)	(1.837)	(0.568)
INSTBD_INS	0.085	-6.406***	-7.596***	-6.491***	-7.680***
	(0.635)	(2.245)	(1.088)	(2.168)	(0.901)
Constant	-0.663	-7.381***	-3.082***	-6.718***	-2.419***
	(0.587)	(1.827)	(0.780)	(1.802)	(0.605)
N		8,367		8,367	
Pseudo R2		0.202		0.202	
Year FE		Yes		Yes	

Table 2.3: The abnormal return test

This table reports the market reaction to the credit and non-credit conferences by using abnormal return. Panel (A) reports the bond filtering process for the treated bond candidates. Panel (B) presents the bond-conference date panel for the treatment group. Panel (C) reports the final bond-conference date panel for the abnormal return with different measures. Panel (D) reports the raw returns for the treatment group and the control group separately. Panels (E) and (F) present the mean and median of the bond market reaction to the credit conference and the non-credit conference respectively. Panel (G) reports the mean of the abnormal return partitioned by the investment/speculative grades. Bonds with a credit rating lower than BBB- (Standard & Poor's rating) are in the speculative-grade group; and BBB- and above are in the investment-grade group. Panel (H) reports the mean of the abnormal return partitioned by the time to maturity of the bond on the conference date. Panels (I) and (J) reports the mean and the median of the abnormal return on the firm level respectively. Panel (K) reports the mean of the abnormal return of the stock market to the credit and the non-credit conference. All returns are on the basis point form. The name of variables start with "RET" and "ABRET" are raw return and signed abnormal return respectively. The letter "D" or "C" in the middle of the variable name stands for "Dirty" or "Clean", suggesting the return (or abnormal return) is calculated with "dirty" price or "clean" price. The suffix "_m1p1", "_m5p5", and "_m10p10" indicates the extended periods of finding pre- and post-conference price to calculate the return. The suffix "_m1p1" requires the pre-conference (post-conference) price must be available on the day prior to (after) the day when the conference occurs, and discard other observations. The suffix "_m5p5" ("_m10p10") extends the days of finding the pre-conference price substitute and the post-conference price substitute to five (ten) trading days before the conference and five (ten) trading days after the conference. To mitigate the correlation between different bonds issued by the same firm, standard errors are clustered by firms (except the median test) and reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Bond filtering process for the treatment group

	Deleted	No. of bonds	No. of firms
As in Panel (A) of Table 2.1: Number of bonds outstanding during the sample period		17,935	2,227
less banking, insurance, utility, and unidentifiable industry	*6,363*		
less putable, preferred, convertible, exchangeable issues	*2,616*		
less foreign currency, Yankee, Canadian bonds	*250*		
less varying- and zero-coupon rate bonds	*445*		
less private placement and perpetual issues	*13*		
less principal amount not $1,000	*36*		
less "day count basis" not "30/360"	*3*		
less interest payment frequency not 1, 2, 4, or 12	*33*		
		8,176	1,102
less bonds not existed on the conference dates (due to bonds mature before the conference date or offered after the conference date)	*620*		
Treated bond candidates		7,556	1,037

Panel (B): Creation of the bond-conference date panel for the treatment group

	Deleted	No. of bond-conference-dates	No. of bonds	No. of firms
Merge treated bond candidates with conference dates		187,468	7,556	1,037
less bond-dates that credit rating is not available	*17,677*			
less bond-dates that credit rating is in default	*545*			
less time-to-maturity over 30 years	*2,484*			
Treated bond-conference date candidates		166,762	6,976	993

Panel (C): Creation of the bond-conference date panel for the abnormal return

_m1p1	Deleted	No. of bond-conf.	No. of bonds	No. of firms
Treated bond-conf. date candidates		166,762	6976	993
less the treated bond price on ±1 day around conf. not available	*114,250*			
Bond-conf. date observations in ***_m1p1*** treatment group		52,512		
less treated bond-date without matching control bonds	*9,022*			
Final ***_m1p1*** abnormal return sample		**43,490**	**4031**	**719**
For credit conferences		1,773	678	232
For non-credit conferences		41,717	3938	686
_m5p5				
Treated bond-conf. date candidates		166,762	6976	993
less the treated bond price on ±5 day around conf. not available	*72,158*			
Bond-conf. date observations in ***_m5p5*** treatment group		94,604		
less treated bond-date without matching control group	*10,497*			
Final ***_m5p5*** abnormal return sample		**84,107**	**4757**	**824**
For credit conferences		3462	1,003	323
For non-credit conferences		80,645	4660	793
_m10p10				
Treated bond-conf. date candidates		166,762	6976	993
less the treated bond price on ±10 day around conf. not available	*62,860*			
Bond-conf. date observations in ***_m10p10*** treatment group		103,902		
less treated bond-date without matching control group	*10,173*			
Final ***_m10p10*** abnormal return sample		**93,729**	**4875**	**851**
For credit conferences		3829	1,075	347
For non-credit conferences		89,900	4768	817

Panel (D): Mean of the raw return

	Credit conference		Non-credit conference	
	Treatment	Control	Treatment	Control
RET_D_m1p1	11.6***	3.71	-1.47*	-3.28***
	(2.87)	(2.64)	(0.75)	(0.60)
RET_C_m1p1	11.4***	3.58	-1.40*	-2.78***
	(3.04)	(2.59)	(0.72)	(0.58)
Observations	*1,773*	*983*	*41,717*	*13,929*
RET_D_m5p5	6.26***	0.91	-6.10***	-7.04***
	(2.11)	(2.02)	(0.69)	(0.49)
RET_C_m5p5	5.90***	1.03	-5.96***	-6.82***
	(2.23)	(1.98)	(0.65)	(0.48)
Observations	*3,462*	*1,798*	*80,645*	*23,053*
RET_D_m10p10	5.18**	-0.023	-8.06***	-9.07***
	(2.11)	(1.99)	(0.73)	(0.49)
RET_C_m10p10	4.87**	0.22	-7.92***	-8.75***
	(2.14)	(1.96)	(0.69)	(0.48)
Observations	*3,829*	*1,973*	*89,900*	*25,148*

Panel (E): Mean of the abnormal return

	Credit conference	Non-credit conference	Difference
ABRET_D_m1p1	12.27***	2.01***	*10.26****
	(3.68)	(0.73)	*(3.73)*
ABRET_C_m1p1	10.72***	1.92***	*8.80***
	(3.79)	(0.66)	*(3.86)*
Observations	*1,773*	*41,717*	*43,490*
ABRET_D_m5p5	8.13***	1.19*	*6.94***
	(2.78)	(0.66)	*(2.80)*
ABRET_C_m5p5	6.65**	1.19*	*5.46**
	(2.84)	(0.64)	*(2.87)*
Observations	*3,462*	*80,645*	*84,107*
ABRET_D_m10p10	8.36***	1.55**	*6.81***
	(3.01)	(0.74)	*(3.02)*
ABRET_C_m10p10	7.53**	1.50**	*6.03***
	(3.02)	(0.73)	*(3.04)*
Observations	*3,829*	*89,900*	*93,729*

Panel (F): Median of the abnormal return

	Credit conference	Non-credit conference	Difference
ABRET_D_m1p1	4.38**	1.51***	*2.87*
	(2.06)	(0.28)	*(2.22)*
ABRET_C_m1p1	2.61	0.74**	*1.87*
	(1.95)	(0.27)	*(2.00)*
Observations	*1,773*	*41,717*	*43,490*
ABRET_D_m5p5	6.78***	2.16***	4.62***
	(1.43)	(0.23)	(1.41)
ABRET_C_m5p5	4.80***	1.24***	*3.56****
	(1.27)	(0.25)	*(1.25)*
Observations	*3,462*	*80,645*	*84,107*
ABRET_D_m10p10	7.72***	2.67***	*5.05****
	(1.57)	(0.26)	*(1.57)*
ABRET_C_m10p10	5.51***	1.72***	*3.79****
	(1.38)	(0.23)	*(1.39)*
Observations	*3,829*	*89,900*	*93,729*

Panel (G): Mean of the abnormal return partitioned by the investment/speculative grade cutoff

	Credit conference		Non-credit conference		Difference	
	Investment grade	Speculative grade	Investment grade	Speculative grade	Investment grade	Speculative grade
ABRET_D_m1p1	0.17	13.06***	0.88	6.70***	*-0.71*	*6.36*
	(12.29)	(3.76)	(0.77)	(1.92)	*(12.06)*	*(4.15)*
ABRET_C_m1p1	8.06	10.94***	1.00	5.84***	*7.06*	*5.09*
	(11.32)	(3.94)	(0.70)	(1.88)	*(11.16)*	*(4.31)*
Observations	*99*	*1,670*	*33,476*	*7968*	*33,575*	*9,638*
ABRET_D_m5p5	0.61	8.80***	0.50	4.22***	*0.11*	*4.58*
	(8.51)	(2.87)	(0.70)	(1.51)	*(8.40)*	*(3.08)*
ABRET_C_m5p5	5.41	6.98**	0.67	3.60**	*4.75*	*3.38*
	(5.93)	(2.97)	(0.67)	(1.52)	*(5.93)*	*(3.22)*
Observations	*163*	*3,283*	*63,278*	*16848*	*63,441*	*20,131*
ABRET_D_m10p10	4.85	8.52***	0.58	5.31***	*4.27*	3.21
	(7.88)	(3.12)	(0.82)	(1.49)	*(7.88)*	(3.22)
ABRET_C_m10p10	9.71	7.41**	0.69	4.67***	*9.02*	*2.74*
	(5.83)	(3.16)	(0.81)	(1.53)	*(5.93)*	*(3.26)*
Observations	*176*	*3,630*	*70,569*	*18729*	*70,745*	*22,359*

Panel (H): Mean of the abnormal return partitioned by time to maturity

	Credit conference		Non-credit conference		Difference	
Time to Maturity	Short	Long	Short	Long	Short	Long
ABRET_D_m1p1	19.35***	3.20	1.20*	2.89**	*18.15****	*0.31*
	(4.55)	(4.75)	(0.65)	(1.23)	*(4.59)*	*(4.81)*
ABRET_C_m1p1	16.89***	2.82	1.21*	2.70**	*15.68****	*0.12*
	(4.91)	(4.40)	(0.62)	(1.15)	*(4.95)*	*(4.49)*
Observations	*996*	*777*	*21,757*	*19,960*	*22,753*	*20,737*
ABRET_D_m5p5	10.20***	5.50	0.73	1.67	*9.48***	*3.83*
	(3.72)	(3.74)	(0.63)	(1.06)	*(3.75)*	*(3.90)*
ABRET_C_m5p5	8.48**	4.32	0.77	1.63	*7.71***	*2.69*
	(3.61)	(3.92)	(0.62)	(1.03)	*(3.65)*	*(4.09)*
Observations	*1,939*	*1,523*	*40,941*	*39,704*	*42,880*	*41,227*
ABRET_D_m10p10	10.68***	5.38	1.12	1.99*	*9.56***	*3.40*
	(3.82)	(3.88)	(0.72)	(1.17)	*(3.81)*	*(4.07)*
ABRET_C_m10p10	9.66***	4.81	1.11	1.90	*8.56***	*2.91*
	(3.68)	(4.01)	(0.72)	(1.17)	*(3.66)*	*(4.21)*
Observations	*2,149*	*1,680*	*45,166*	*44,734*	*47,315*	*46,414*

Panel (I): Mean of the abnormal return on the firm level

	Credit conference	Non-credit conference	Difference
ABRET_D_m1p1	14.49***	2.03**	*12.45***
	(4.80)	(0.92)	*(4.84)*
ABRET_C_m1p1	14.54***	2.31***	*12.24****
	(4.70)	(0.87)	*(4.74)*
Observations	*820*	*11,836*	*12,656*
ABRET_D_m5p5	7.74**	1.49*	*6.25**
	(3.56)	(0.83)	*(3.63)*
ABRET_C_m5p5	7.17**	1.63**	*5.54*
	(3.61)	(0.82)	*(3.69)*
Observations	*1,433*	*19,281*	*20,714*
ABRET_D_m10p10	6.52*	1.51*	*5.01*
	(3.67)	(0.88)	*(3.75)*
ABRET_C_m10p10	6.51*	1.49*	*5.02*
	(3.61)	(0.87)	*(3.70)*
Observations	*1,575*	*20,855*	*22,430*

Panel (J): Median of the abnormal return on the firm level

	Credit conference	Non-credit conference	Difference
ABRET_D_m1p1	6.26**	1.39***	*4.87**
	(2.82)	(0.50)	*(2.87)*
ABRET_C_m1p1	3.57	0.94*	*2.63*
	(2.76)	(0.53)	*(2.86)*
Observations	*820*	*11,836*	*12,656*
ABRET_D_m5p5	6.25***	1.69***	*4.56***
	(2.15)	(0.51)	*(2.32)*
ABRET_C_m5p5	4.70**	1.14**	*3.56*
	(2.34)	(0.53)	*(2.37)*
Observations	*1,433*	*19,281*	*20,714*
ABRET_D_m10p10	7.66***	2.12***	*5.54****
	(2.17)	(0.53)	*(2.13)*
ABRET_C_m10p10	7.59***	1.16**	*6.43****
	(2.26)	(0.54)	*(2.32)*
Observations	*1,575*	*20,855*	*22,430*

Panel (K): Mean of stock return to different types of conferences

	Treatment	CRSP value weighted index	Abnormal return
Credit Conference	0.05	14.02	-1.73
	(9.54)	(9.51)	(8.34)
Observations	*1421*	*197*	*1421*
Non-credit Conference	18.47***	9.13**	10.34***
	(2.42)	(3.59)	(1.95)
Observations	*20718*	*1656*	*20718*

Table 2.4: The trading volume test

This table reports the market reaction to the conferences by using trading volume as the measure of the market reaction. The dependent variable is either raw trading volume (*RawVol*) or abnormal trading volume (*AbnVol*). Raw trading volume (*RawVol*) is defined as the dollar value of aggregated trading volume on each trading day scaled by the bond offering amount, and then aggregated to the firm level. We set the value of *RawVol* to zero when there is no trade within a day. Abnormal trading volume (*AbnVol*) is the difference between the raw trading volume and the mean of the firm's raw trading volume six months before the conference. *CredConf* (or *NoncConf*) is a dummy variable with the value of one if the firm attends a credit conference (or non-credit conference) on the day and the next five trading days, and zero otherwise. *Specu* is a dummy variable with the value of one if the firm's average credit rating is below BBB- on the conference day, and zero otherwise. *EarnAnn* is the dummy variable for the earnings announcement. *NegEarn* is the dummy variable for firms announcing negative earnings. *AnBuy* is the dummy variable for financial analysts providing "buy" recommendations. *AnSell* is the dummy variable for financial analysts providing "sell" recommendations. *AnConflicts* is the dummy variable when different financial analysts providing conflict recommendations. *AnReport* is the dummy variable when financial analysts provide any recommendations or forecasts. *RatUp* is the dummy variable when a firm's credit rating is upgraded. *RatDown* is the dummy variable when a firm's credit rating is downgraded. These events are studied in De Franco et al. (2009) and Easton et al. (2009). *BondSize* is the average value of all bonds' outstanding within a firm in the logarithm form. *MVE* is the market value of equity in the logarithm form. *STVolume* is the stock trading volume scaled by total share outstanding. Panel (A) reports the sample creation process. Panel (B) presents the number of conference dates within the final sample. Panel (C) presents descriptive statistics. Panels (D) and (E) report the regression results with different specifications. Standard errors are clustered by firms and dates, and reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Trading volume sample creation

	Deleted	No. of bonds	No. of firms
As in Panel (A) of Table 2.1: Number of bonds outstanding during the sample period		17,935	2,227
less banking, insurance, utility, and unidentifiable industry	*6,363*		
less putable, preferred, convertible, exchangeable issues	*2,616*		
less foreign currency, Yankee, Canadian bonds	*250*		
less varying- and zero-coupon rate bonds	*445*		
less private placement and perpetual issues	*13*		
less principal amount not $1,000	*36*		
Remaining sample		8,212	1,102

	Deleted	No. of firm-day	No. of firms
Merge the remaining sample with conference dates and enhanced TRACE, and expand it into the firm-(trading) day panel for the entire sample period. When no trade on a (trading) day, set value to zero		2,209,984	1,102
less firm-day when the firm is in default	*7,129*		
Final sample for the trading volume analysis		2,202,855	1,101

Panel (B): Description of conference dates in the final trading volume sample

	No. of firm-days	Percent	No. of firms
Credit conference day	2,377	0.11%	472
Non-credit conference day	30,245	1.37%	992
No conference	2,170,233	98.52%	
Total	2,202,855		
Credit conference day and next five trading days (*CredConf*)	14,096	0.64%	472
Non-credit conference day and next five trading days (*NoncConf*)	165,075	7.49%	992
No conference	2,023,684	91.87%	
Total	2,202,855		

Panel (C): Statistical description

Variable	n	Mean	S.D.	Min	0.25	Median	0.75	Max
RawVol	2,202,855	0.30	0.77	0	0	0	0.21	5.07
AbnVol	1,773,945	-0.09	0.87	-2.19	-0.40	-0.18	-0.01	4.90
CredConf	2,202,855	0.01	0.08	0	0	0	0	1
NoncConf	2,202,855	0.07	0.26	0	0	0	0	1
Specu	2,202,855	0.48	0.5	0	0	0	1	1
EarnAnn	2,202,855	0.07	0.26	0	0	0	0	1
NegEarn	2,202,855	0.01	0.09	0	0	0	0	1
AnBuy	2,202,855	0.08	0.27	0	0	0	0	1
AnSell	2,202,855	0.02	0.13	0	0	0	0	1
AnConflicts	2,202,855	0.01	0.08	0	0	0	0	1
AnReport	2,202,855	0.16	0.36	0	0	0	0	1
RatUp	2,202,855	0.00	0.06	0	0	0	0	1
RatDown	2,202,855	0.00	0.06	0	0	0	0	1
BondSize	2,202,855	12.68	0.65	8.52	12.24	12.65	13.12	14.32
MVE	1,893,767	8.09	1.73	3.69	6.99	8.09	9.26	12.10
STVolume	1,686,134	0.01	0.01	0	0	0.01	0.01	0.06

Panel (D): Trading volume regression

Volume=	Raw trading volume			Abnormal trading volume		
	i	ii	iii	iv	v	vi
CredConf	0.168***	0.077***	0.024*	0.049***	0.039**	0.043***
	(0.022)	(0.019)	(0.014)	(0.015)	(0.016)	(0.016)
NoncConf	0.081***	0.001	0.000	0.019***	0.001	0.003
	(0.007)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
EarnAnn		-0.001	0.002		0.038***	0.025***
		(0.005)	(0.004)		(0.004)	(0.004)
NegEarn		0.129***	0.120***		0.096***	0.106***
		(0.024)	(0.017)		(0.017)	(0.017)
AnBuy		-0.019***	-0.020***		-0.011**	-0.010*
		(0.006)	(0.005)		(0.005)	(0.005)
AnSell		0.031***	0.028***		0.023**	0.025***
		(0.012)	(0.010)		(0.009)	(0.009)
AnConflicts		0.064***	0.059***		0.067***	0.067***
		(0.017)	(0.016)		(0.017)	(0.016)
AnReport		0.020***	0.016***		0.005	0.009**
		(0.004)	(0.004)		(0.004)	(0.004)
RatUp		0.140***	0.118***		0.171***	0.167***
		(0.023)	(0.022)		(0.024)	(0.024)
RatDown		0.397***	0.342***		0.297***	0.295***
		(0.032)	(0.030)		(0.032)	(0.032)
BondSize		0.125***	0.212***		-0.005	-0.009
		(0.012)	(0.023)		(0.007)	(0.015)
MVE		0.023***	-0.009		0.005*	0.027***
		(0.006)	(0.009)		(0.003)	(0.007)
STVolume		7.947***	8.045***		4.201***	6.842***
		(0.548)	(0.450)		(0.345)	(0.389)
Observations	2,202,855	1,601,386	1,601,386	1,773,945	1,424,592	1,424,590
Adjusted R2	0.001	0.056	0.099	0.000	0.021	0.033
Difference P-value	0.000	0.000	0.090	0.050	0.019	0.013
Firm FE	No	No	Yes	No	No	Yes
Industry FE	No	Yes	No	No	Yes	No
Rating FE	No	Yes	Yes	No	Yes	Yes
Day FE	No	Yes	Yes	No	Yes	Yes

Panel (E): Raw trading volume regression with interaction variables

	i	ii	iii
CredConf	-0.107***		-0.108***
	(0.038)		(0.038)
CredConf × Specu	0.140***		0.141***
	(0.041)		(0.041)
NoncConf		0.005	0.005
		(0.004)	(0.004)
NoncConf × Specu		-0.010	-0.011
		(0.007)	(0.007)
Specu	0.089***	0.090***	0.090***
	(0.018)	(0.018)	(0.018)
EarnAnn	0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)
NegEarn	0.123***	0.123***	0.123***
	(0.018)	(0.018)	(0.018)
AnBuy	-0.020***	-0.020***	-0.020***
	(0.005)	(0.005)	(0.005)
AnSell	0.028***	0.028***	0.028***
	(0.010)	(0.010)	(0.010)
AnConflicts	0.059***	0.059***	0.059***
	(0.016)	(0.016)	(0.016)
AnReport	0.015***	0.015***	0.015***
	(0.004)	(0.004)	(0.004)
RatUp	0.119***	0.119***	0.119***
	(0.022)	(0.022)	(0.022)
RatDown	0.349***	0.349***	0.349***
	(0.030)	(0.030)	(0.030)
BondSize	0.220***	0.220***	0.220***
	(0.024)	(0.024)	(0.024)
MVE	-0.010	-0.010	-0.010
	(0.009)	(0.009)	(0.009)
STVolume	8.054***	8.053***	8.054***
	(0.453)	(0.453)	(0.453)
Observations	1,601,386	1,601,386	1,601,386
Adjusted R2	0.098	0.098	0.098
Firm Fixed Effect	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes

Table 2.5: The change in the yield spread on the secondary market

This table presents the results for the regression of the change in the secondary market bond yield spread around the month when a firm attends a credit (or non-credit) conference. *Ch.YSpread* is the change in the yield spreads from the previous three month to the next three months (-3 month to +3 month). *YSpread* is the difference between the monthly yield-to-maturity of each bond and the maturity-matched Treasury yield, aggregated to the firm level with the weight of the offering amount. Monthly yield-to-maturity is the median yield of all transactions occurring on the last active trading day within a month. Maturity-matched Treasury yield are computed by linearly interpolating benchmark Treasury yields in Federal Reserve H-15. *CreditConfM* (*NoncConfM*) is the dummy variable, and takes a value of one if the firm attends at least one credit (non-credit) conference within a month. *Ch.RatingM* is the change in the average credit rating within a firm from the previous three months to the next three months. *Ch.BondValueM* is the change in the total bond value (in the logarithm form) within a firm from the previous three months to the next three months. *Ch.NumBondsM* is the change in the number of bonds outstanding within a firm from the previous three months to the next three months. *Ch.MaturityM* is the change in the average time to maturity of all bonds outstanding within a firm from the previous three months to the next three months. *Ch.RetVolM* is the change in the issuer's market-adjusted stock return volatility from the previous three months to the next three months. *Ch.TAM* is the change in total assets in the logarithm form from the previous quarter to the next quarter. *Ch.LevM* is the change in financial leverage from the previous quarter to the next quarter. Financial leverage is total liabilities scaled by total assets. *Ch.CashM* is the change in the cash and short-term investments holding scaled by total assets from the previous quarter to the next quarter. *Ch.ROAM* is the change in return on total assets for the preceding four quarters from the previous quarter to the next quarter. Panel (A) presents descriptive statistics. Panels (B) reports regression results with different specifications. Standard errors are clustered by firms, and reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Data description

Variable	n	Mean	S.D.	Min	.25	Median	.75	Max
Ch.YSpread	147,479	0.44	4.35	-11.83	-0.6	-0.01	0.59	29.94
CreditConfM	167,113	0.01	0.10	0	0	0	0	1
NoncConfM	167,113	0.11	0.32	0	0	0	0	1
Ch.RatingM	156,266	-0.04	0.50	-2.5	0	0	0	2
Ch.BondValueM	162,995	0.02	0.17	-0.61	0	0	0	0.77
Ch.NumBondsM	162,995	0.03	1.17	-3.99	-0.38	0	0.37	5.06
Ch.MaturityM	162,995	-2.66	9.25	-12	-6	-6	-6	49.5
Ch.RetVolM	78,753	0	0.01	-0.05	0	0	0	0.06
Ch.TAM	67,432	0.02	0.10	-0.32	-0.02	0.01	0.05	0.44
Ch.LevM	67,382	0	0.08	-0.27	-0.03	0	0.03	0.34
Ch.CashM	67,382	0	0.04	-0.14	-0.01	0	0.01	0.15
Ch.ROAM	66,969	0	0.05	-0.19	-0.03	0	0.03	0.17

Panel (B): Regression results

	Full Sample			Restricted Sample		
	i	ii	iii	iv	v	vi
CreditConfM	-0.276**	-0.313***	-0.195**	-0.184*	-0.253***	-0.200**
	(0.110)	(0.096)	(0.093)	(0.107)	(0.095)	(0.095)
NoncConfM	-0.333***	-0.017	0.003	-0.185***	0.005	-0.001
	(0.039)	(0.031)	(0.031)	(0.041)	(0.032)	(0.032)
Ch.RatingM		-0.883***	-0.626***		-0.808***	-0.632***
		(0.086)	(0.085)		(0.089)	(0.091)
Ch.BondValueM		-0.261	-0.126		-0.301*	-0.076
		(0.170)	(0.172)		(0.171)	(0.163)
Ch.NumBondsM		0.028	0.041		0.035	0.040
		(0.037)	(0.036)		(0.039)	(0.036)
Ch.MaturityM		-0.001	0.001		0.000	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
Ch.RetVolM		0.723***	0.667***		0.687***	0.684***
		(0.043)	(0.041)		(0.045)	(0.042)
Ch.TAM			-3.594***			-3.575***
			(0.455)			(0.461)
Ch.LevM			3.170***			3.095***
			(0.493)			(0.499)
Ch.CashM			-0.033			-0.106
			(0.477)			(0.483)
Ch.ROAM			-1.212**			-1.175**
			(0.530)			(0.539)
Observations	147,479	76,408	63,823	69,753	64,928	60,513
Adjusted R2	0.001	0.331	0.341	0.001	0.330	0.345
NumCredit	1,802	1,594	1,420	1,802	1,594	1,420
NumNonCredit	18,740	17,069	16,291	18,740	17,069	16,291
Industry FE	No	Yes	Yes	No	Yes	Yes
Month-year FE	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes

Table 2.6: The change in bond institutional ownership

This table presents the results for the regressions of the change in bond institutional investor ownership around the quarter when firms attend credit (or non-credit) conferences. The dependent variable is *Ch.InstALL*, *Ch.InstMUT*, or *Ch.InstINS*, which are the changes in the overall bond institutional investor ownership, the mutual fund ownership, and the insurance company ownership. *CreditConfQ* and *NoncConfQ* are the dummy variables with the value of one when a firm attends at least one credit conference or non-credit conference within a quarter, and zero otherwise. *Ch.RatingQ* is the change in the credit rating. *Ch.NumTradeQ* is the change in the number of trades in the logarithm form. *Ch.VolTradeQ* is the change in the total dollar value of aggregated trading volume within a quarter scaled by the bond issue size. *Ch.RetVolQ* is the change in the market adjusted stock return volatility. *Ch.MVEQ* is the change in market value of equity in the logarithm form. *Ch.LevQ* is the change in financial leverage. *Ch.CashQ* is the change in cash and short-term investment scaled by total assets. All changes are calculated by using value in the next quarter minus the value from the previous quarter. Panel (A) presents descriptive. Panels (B) and (C) outline the results with different partitions. All the regressions are clustered at the firm (issuer) level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Data description

Variable	n	Mean	S.D.	Min	0.25	Median	0.75	Max
Ch.InstALL	121,002	-1.80	9.68	-50.53	-2.74	-0.06	0.92	25.12
Ch.InstMUT	104,010	-0.75	6.59	-32.15	-1.82	0.00	1.21	18.87
Ch.InstINS	96,190	-0.74	4.25	-20.61	-1.36	0.00	0.49	11.65
CreditConfQ	121,002	0.05	0.22	0.00	0.00	0.00	0.00	1.00
NoncConfQ	121,002	0.53	0.50	0.00	0.00	1.00	1.00	1.00
Ch.RatingQ	111,285	-0.03	0.45	-2.00	0.00	0.00	0.00	2.00
Ch.NumTradeQ	121,002	-0.07	0.82	-3.64	-0.34	0.00	0.22	2.48
Ch.VolTradeQ	121,002	-4.45	24.75	-141.79	-6.33	0.00	2.13	56.28
Ch.RetVolQ	95,422	0.00	0.01	-0.04	-0.00	-0.00	0.00	0.05
Ch.MVEQ	96,578	0.02	0.27	-1.02	-0.09	0.04	0.16	0.73
Ch.LevQ	96,350	0.00	0.08	-0.29	-0.03	-0.00	0.03	0.30
Ch.CashQ	96,348	-0.00	0.04	-0.15	-0.01	0.00	0.01	0.13

Panel (B): Main regression results

Dep.Var	All			Mutual fund			Insurance company		
	i	ii	iii	iv	v	vi	vii	viii	ix
CreditConfQ	-1.051***	0.462**	0.419**	-1.181***	0.368**	0.315*	-0.138*	-0.085	-0.035
	(0.180)	(0.202)	(0.209)	(0.144)	(0.158)	(0.163)	(0.084)	(0.065)	(0.065)
NoncConfQ	0.596***	0.018	-0.085	0.342***	0.017	-0.018	0.318***	-0.020	-0.065
	(0.093)	(0.098)	(0.093)	(0.076)	(0.073)	(0.073)	(0.049)	(0.056)	(0.055)
Ch.RatingQ		0.628***	0.721***		0.239***	0.326***		0.365***	0.375***
		(0.124)	(0.132)		(0.091)	(0.093)		(0.061)	(0.065)
Ch.NumTradeQ		1.832***	1.965***		1.185***	1.267***		0.371***	0.396***
		(0.108)	(0.120)		(0.076)	(0.085)		(0.032)	(0.036)
Ch.VolTradeQ		-0.039***	-0.043***		-0.024***	-0.026***		-0.011***	-0.012***
		(0.002)	(0.002)		(0.001)	(0.001)		(0.001)	(0.001)
Ch.RetVolQ			20.384***			11.238***			-11.505***
			(5.414)			(4.015)			(2.523)
Ch.MVEQ			-0.100			-0.075			-0.149
			(0.219)			(0.167)			(0.107)
Ch.LevQ			-0.559			-0.084			0.355
			(0.687)			(0.492)			(0.328)
Ch.CashQ			-3.163***			-3.176***			0.503
			(1.175)			(0.848)			(0.665)
Observations	121,002	111,260	89,780	104,010	96,701	78,213	96,190	91,818	74,477
Adjusted R2	0.001	0.074	0.082	0.002	0.062	0.067	0.001	0.082	0.087
NumCredit	6,116	5,456	5,079	6,116	5,456	5,079	6,116	5,456	5,079
NumNonCredit	64,095	61,449	59,854	64,095	61,449	59,854	64,095	61,449	59,854
Firm FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Rating FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Maturity FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Panel (C): Regressions partitioned by speculative-grade bonds and by investment-grade bonds

	Speculative grade only			Investment grade only		
Dep.Var	All	Mutual fund	Insurance company	All	Mutual fund	Insurance company
	i	ii	iii	iv	v	vi
CreditConfQ	0.489**	0.361**	-0.048	-0.577	-1.019	0.102
	(0.213)	(0.165)	(0.063)	(0.721)	(0.773)	(0.379)
NoncConfQ	-0.162	-0.128	-0.100	-0.046	0.016	-0.045
	(0.156)	(0.134)	(0.062)	(0.112)	(0.082)	(0.073)
Ch.RatingQ	0.847***	0.463***	0.395***	0.452***	0.086	0.304***
	(0.189)	(0.150)	(0.076)	(0.163)	(0.092)	(0.099)
Ch.NumTradeQ	4.167***	2.856***	0.647***	1.008***	0.551***	0.300***
	(0.204)	(0.143)	(0.056)	(0.091)	(0.058)	(0.043)
Ch.VolTradeQ	-0.066***	-0.044***	-0.010***	-0.035***	-0.020***	-0.012***
	(0.004)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Ch.RetVolQ	5.049	-9.870	0.993	32.939***	30.509***	-26.752***
	(8.366)	(6.179)	(2.499)	(5.696)	(3.876)	(3.935)
Ch.MVEQ	0.223	0.002	0.113	-0.479*	-0.022	-0.401**
	(0.312)	(0.245)	(0.105)	(0.265)	(0.189)	(0.186)
Ch.LevQ	-1.981*	-1.002	-0.210	1.016	0.787	1.066**
	(1.066)	(0.845)	(0.342)	(0.849)	(0.526)	(0.492)
Ch.CashQ	-3.389*	-4.536***	0.717	-3.622**	-2.974***	0.659
	(2.052)	(1.592)	(0.723)	(1.409)	(0.929)	(0.915)
Observations	28,204	24,476	20,677	61,573	53,731	53,794
Adjusted R2	0.078	0.078	0.086	0.108	0.063	0.102
NumCredit	4,912	4,912	4,912	167	167	167
NumNonCredit	16,416	16,416	16,416	43,438	43,438	43,438
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
Maturity FE	Yes	Yes	Yes	Yes	Yes	Yes

Chapter 3

The interactive effect of firms' R&D intensity and analysts' educational background on analysts' behavior: Evidence from the chemical manufacturing industry

3.1 Introduction

This paper studies how sell-side analysts' educational background affects their coverage decision and forecasting behavior in an industry with a high level of technological complexity.[74] Sell-side analysts play an important role in the capital market by gathering and disseminating information to the market. Prior literature documents a number of factors that affect analysts' coverage decision and quality of their activities such as earnings forecasts and stock recommendations. These factors can be categorized into the firm related and the analyst related. For example, analysts' earnings forecast accuracy is a function of information and predictability of the underlying firm, as well as skills and incentives of the analyst who gives the forecast (Pope 2003). On the firm side, firms' information and predictability capture the quality of inputs for the forecasting model. The extant literature documents that firms' market value of equity, the institutional investor ownership, information disclosure, future prospects, location, and business complexity are associated with analysts' coverage decision and forecast accuracy (Bhushan 1989; O'Brien and Bhushan 1990; McNichols and O'Brien 1997; Lang and Lundholm 1996; Jennings et al. 2017; O'Brien and Tan 2015; Barth et al. 2001; Gu and Wang 2005; Amir et al. 2003). Gu and Wang (2005) and Amir et al. (2003) use R&D intensity to measure firms' complexity, and find that analysts' forecast accuracy is negatively associated with the R&D investment. Relatedly, Barth et al. (2001) analyze the benefit and cost for analysts covering firms with a high level of complexity, and document a positive association between analyst following and the level of firms' R&D investment, indicating that the benefit of covering highly intense R&D firms outweighs the cost.

[74] I use "analyst coverage" and "analyst following" interchangeably. Both terms mean the number of analysts following a firm.

Skills and incentives are the analyst related factors affecting analysts' coverage decision and forecast behavior. Controlling for the aforementioned firm characteristics, a wide array of papers document individual analysts' characteristics affecting analysts' behavior, including general and firm-specific experience (Clement 1999), career concern (Hong and Kubik 2003; Hong et al. 2000), analysts' geographical location (Malloy 2005; Bae et al. 2008), social connections with firms' executives (Cohen et al. 2010), encounters with management in broker-hosted investor conferences (Green et al. 2014b), being affiliated underwriting analysts (Fang 2005; Cowen et al. 2006; Cliff and Denis 2004), political preference (Jiang et al. 2016), industry knowledge (Kadan et al. 2012; Bradley et al. 2017) and so forth. In Bradshaw (2011) and Brown et al. (2015), both papers use survey data and find that the most important trait of sell-side analysts valued by institutional investors is industry knowledge. In addition, Bradley et al. (2017) use analysts' employment history as a proxy of industry knowledge to study the association between analysts' industry knowledge and their forecasting behavior. They find that an analyst who covers firms in an industry in which she has previous work experience outperforms her counterparts without such relevant employment history on forecast accuracy, market reactions to forecast revisions, and career prospects. Industry knowledge is imperative to analysts. Having said that, the contribution of industry knowledge to analysts' performance may vary across firms within the industry. The cross-sectional variations of firm-specific complexity may reinforce or undermine the importance of analysts' industry knowledge.

In this paper, I combine the firm related (firms' technological complexity) and the analyst related (industry knowledge) factors and study the interactive effect of the two on analysts' behavior. Specifically, I focus on the chemical manufacturing industry, and use the amount of firms' R&D investment – relative to their industry peers – to measure its technological complexity. In addition, I use a new proxy for analysts' industry knowledge: the educational degree that an analyst holds. The reasons that I choose the chemical manufacturing industry and analysts' educational degrees are as follows: (1) firms in this industry have sufficient cross-sectional variations in the amount of R&D relative to their industry peers within a year, thus allowing for effective differentiation of technological complexity across firms; and (2) analysts' educational degree is convincing for the analyst possessing industry knowledge (technological knowledge in this context). For instance, an analyst with a BSc in Chemical Engineering is more likely to be skilled to analyze firms in the chemical manufacturing industry than one without such degree does.

Elaborating on this theme, I exploit a sample containing 1,118 firms in the chemical manufacturing industry (SIC 2800 – 2899) for the period from 2003 to 2016, and the educational qualifications of 1,218 sell-side analysts covering those firms during the sample period. Among these 1,218 analysts, 440 analysts have a technological degree related to chemistry (matching analysts), 703 analysts have non-technological degrees (non-matching analysts), and 75 analysts have other technological degrees unrelated to chemistry (irrelevant analysts).

As my starting point, I test the association between the type of analysts' education degrees and the number of industries they follow. An analyst with a matching technological degree may have more technological knowledge of an industry that matches with her degree. On this account, the employing brokerage house is more likely to assign her the matched industry over other analysts who do not have technological degrees. Based on this argument, I predict and find that analysts having a matching degree cover less industries.

My second hypothesis is motivated by Barth et al. (2001), who document the benefit and the cost for analysts following firms with a high level of intangible assets (including R&D, advertising expense, and intangible assets on the balance sheet) and find that analyst coverage is positively associated with the amount of firms' R&D intensity. This indicates that the benefit of covering a complex firm outweighs the cost. But analysts are not homogenous. The net benefit may vary with analysts' ability to analyze complex technological information. Against the background of the chemical manufacturing industry, I argue that analysts with matching technological degrees more likely generate a positive net benefit for the coverage of R&D-intensive firms. Consistent with my hypothesis, the empirical result presents a positive (negative) association between firms' matching (non-matching) analyst following and R&D intensity.

The third hypothesis builds on the contention that firms' complexity and uncertainty have a negative impact on analysts' forecast accuracy, with Gu and Wang (2005) finding that analysts' forecast accuracy is negatively associated with the amount of R&D investment and the level of firms' balance-sheet intangible assets. The degree of R&D intensity in a firm reflects the level of technological complexity. However, the complexity related to balance-sheet intangible assets is less likely ascribable to the technology as the balance-sheet intangible assets are mainly goodwill and brand recognition. Analysts with a matching degree may possess better understanding of technological knowledge, and generate better forecasts than non-matching analysts when the firm has a high degree of technological complexity. In contrast, the technological degree may fall short to analyze firms with the greater amount of balance-sheet intangible assets. Accordingly, I argue and find that matching analysts ameliorate the negative association between forecast accuracy and firms' complexity only when the complexity is due to technology, rather than balance-sheet intangible assets.

Fourth, I expect that the market rewards analysts with a matching educational degree. To test this hypothesis, I use five-day cumulative abnormal return to analysts' recommendation revisions. Consistent with my expectation, the market reaction to matching analysts' recommendation revisions is greater than that to non-matching analysts. However, the result holds only for upward revisions. Furthermore, I also find that the market reaction to matching analysts' recommendation revisions increases with firms' R&D intensity.

Lastly, I test whether matching analysts issue bolder earnings forecasts than non-matching analysts for firms with intensive R&D investment. I restrict the sample to pharmaceutical firms only (SIC from 2833 to 2836) which account for over eighty percent of all the firms in this industry.[75] By using a logistic model, I find a negative association between firms' R&D intensity and analysts' boldness, and analysts' matching degree mitigates such negative association.

My paper contributes the literature as follows. The first contribution speaks to the analyst literature in terms of the impact of analysts' industry knowledge on their coverage decision and forecast behavior. Survey evidence shows that institutional investors value analysts' industry knowledge as the most important trait (Brown et al. 2015; Bradshaw 2011). However, there is a paucity of empirical evidence that specifically studies analysts' industry knowledge. So far, only Bradley et al. (2017)

[75] The figure can be calculated in Panel (B), Table 3.1.

find a way to define industry knowledge and provide empirical evidence to the impact of analysts' industry knowledge on their performance. My paper provides insights into how the importance of analysts' industry knowledge varies with the level of firms' (technological) complexity. I find an interactive effect of analysts' industry knowledge and firms' complexity on their coverage decision and forecasting behavior.

My paper also contributes to the literature relating to education in the realm of the capital market. Some papers that study the impact of educational background touch on the level or the quality of the educational degree – such as Chevalier and Ellison (1999) finding that mutual managers who attended high-SAT undergraduate institutions have higher risk-adjusted excess return, and Falato et al. (2015) finding that CEOs graduated from prestige institutions receive a premium in pay – with these papers using educational degrees as a proxy of unobservable ability. Additionally, several papers pertain to the type of educational degrees, including Tyler and Steensma (1998) and Barker and Mueller (2002) that find the type of an educational degree (science- or engineering-related degrees versus business degrees) that a CEO holds influences the funding of firms' R&D. My paper builds on this research, investigating the education effect in the context of capital market on analysts' behavior to shed lights on how the specific knowledge of an educational degree is transferred into analysts' performance.

The remainder of this study is organized as follows. In the next section, I discuss the related literature and develop the hypotheses. In Section 3, I outline the research design and variables I need. Section 4 presents the various sources of data collection and the general sample description. Section 5 reports the primary results and findings. Section 6 concludes.

3.2 Literature review and hypotheses

I build on the literature that studies the impact of firms' (technological) complexity spurred by R&D (firm-related factors) and analysts' individual characteristics (analyst-related factors) on analysts' coverage decision and forecast behavior.

3.2.1 Firm-related factors

Firm-related factors that influence analysts' behavior include the market value of equity, institutional investor ownership, stock return volatility, future prospects, information disclosure, firms' location, intangible assets, and so forth (O'Brien and Bhushan 1990; McNichols and O'Brien 1997; Lang and Lundholm 1996; O'Brien and

Tan 2015; Jennings et al. 2017; Barth et al. 2001; Gu and Wang 2005; Amir et al. 2003). Barth et al. (2001) study the association between analyst coverage and firms' intangible assets (R&D, advertising expense, and intangible assets on the balance sheet). They argue that firms with more R&D investment are more likely to be mispriced, and mispriced firms may incentivize analyst following. Notwithstanding, analysts' cost of covering firms with a high level of R&D investment may not be trivial for a number of reasons. Firstly, R&D-intensive firms have greater information asymmetry than firms with less R&D (Aboody and Lev 2000; Boone and Raman 2001; Barth and Kasznik 1999). The great information asymmetry may impede analysts' information acquisition. Secondly, prior studies highlight the deficiency of financial reporting in R&D-intensive industries such as wireless communication or biotech. Amir and Lev (1996) focus on the wireless communication industry and find that financial information is largely value irrelevant. Xu et al. (2007) and Callen et al. (2010) find that non-financial information is value relevant for bio-tech firms after controlling for financial information. Thirdly, firms with greater R&D investments would have greater uncertainties. Kothari, Laguerre and Leone (2002) compare the uncertainties of future benefits generated by capital investment and by R&D investment, and find the latter is thrice as large as the former. In light of the greater information asymmetry, less relevant financial information, and greater uncertainty in R&D-intensive firms, covering such firms would be costlier. Barth et al. (2001) present a positive association between firms' analyst following and R&D investment, indicating that the benefit of covering firms with substantial R&D investment outweighs the cost on average. In addition, Gu and Wang (2005) investigate the impact of firms' intangible assets (including R&D, advertising expense, and intangible assets on the balance sheet) on analysts' forecast accuracy. They find that firms with more intangible assets are associated with more complex information and uncertainty, which complicates analysts' earnings forecast activities, leading to a decrease in their forecast accuracy.

3.2.2 Analyst-related factors

The literature that explores the influence of analyst-related factors on analysts' behavior is substantial. Papers find that analysts' forecasting behavior is linked to their general and firm-specific experience, the size of the employing brokerage house, the numbers of firms and industries they follow, innate ability, personal conservatism, location, social connection with the executives of the firms they cover, private incentives, industry knowledge, and so on (Clement 1999; De Franco and Zhou 2009; Jiang et al. 2016; Malloy 2005; Bae et al. 2008; Cohen et al. 2010; Lin and McNichols 1998; Michaely and Womack 1999; Cowen et al. 2006; Jackson 2005; Jacob et al. 2008; Francis and Philbrick 1993). The review paper of Bradshaw (2011) and the survey paper of Brown et al. (2015) show the importance of analysts' industry knowledge. Specifically, in Bradshaw (2011), the author demonstrates a number of analysts' traits valued by institutional investors. Among other traits presented in the survey with rankings varying across the time, industry knowledge has always been the top trait all the time. In line with Bradshaw (2011), Brown et al. (2015) conduct a comprehensive survey of 365 sell-side analysts, and find that analysts themselves believe that industry knowledge is the most important skill. Boni and Womack (2006) and Kadan et al. (2012) find that analysts have superior ability to select and rank individual stocks within the industry. However, there is still a paucity of empirical evidence that specifically studies analysts' industry knowledge, mainly because of the difficulty of measuring industry knowledge. So far, only Bradley et al. (2017) find a way to define industry knowledge. In Bradley et al. (2017), the authors use pre-analyst employment history as the proxy of the analyst possessing industry knowledge, and find that an analyst with previous experience in the industry that matches her coverage portfolio tends to generate more accurate forecasts, evoke stronger market reactions to forecast revisions, and have a better career path than their peer analysts who do not have such experience.

3.2.3 Educational background

In the domain of the education literature, some papers focus on the level or the quality of the degrees, such as comparing bachelor degrees to master degrees, or the reputation between the degree-awarding institutions. Frey and Detterman (2004) find that CEOs have greater managerial ability if they are graduated from schools requiring higher scores in the entrance exam. Along similar lines, Chevalier and Ellison (1999) provide evidence that mutual fund managers who attended higher-SAT schools have higher risk-adjusted excess returns. Falato et al. (2015) find that CEOs who graduated from prestige institutions receive a premium in pay. Miller et al. (2015) find that the differences in CEOs' skill sets can be attributed to the levels and quality of the awarding institutions. These studies use educational degrees as a proxy of the underlying persons' unobservable ability. A person having a higher level or quality degree is indicative of better ability, which could be translated into better performance. Relatedly, in the financial analyst literature, De Franco and Zhou (2009) use the Chartered Financial Analyst (CFA) designation to be a proxy of analysts' unobservable innate ability, and find that CFA analysts issue bolder and timelier forecasts than their peers without CFA.

Another stream of the education literature in the capital market considers the type or the content of educational degrees. Hitt and Tyler (1991) document that the type of CEOs' educational background (liberal arts or engineering) is related to the information that they use in the evaluation of strategic decisions. Tyler and Steensma (1998) find that CEOs with a technical educational degree emphasize more on the opportunities provided by strategic alliance than those with a non-technical degree. In addition, Barker and Mueller (2002) find that a CEO that holds a technical degree spends significantly more on R&D than other CEOs without such a degree. Similarly, King et al. (2016) find that bank CEOs with an MBA degree exhibit better performance than their peers with bachelor degrees or PhD degrees, suggesting that business knowledge matters more in doing management work than technical expertise.

My paper adds to literature by studying the interactive effect of analysts' educational degrees and firms' R&D on their coverage decision and forecast behavior. Specifically, I establish the research within the chemical manufacturing industry (SIC 2800 – 2899). Firms in this industry have significant variations in R&D investment relative to their industry peers. Firms with more R&D investment may require analysts to have more knowledge specific to this technology. A matching educational degree may satisfy this requirement.[76] I define a "matching degree" as one with a title including the following words: chemical, chemistry, biology, biochemistry, medical, medicine, pharmacy, or Doctor of Medicine (MD). Analysts with a matching degree are matching analysts. Concomitantly, analysts only with business degrees (accounting, finance, management or economics), other social science degrees, or

[76] An anecdotal evidence supports this assumption: "…When you're looking at life science companies, both large and small, the big questions are, will the drug or device they're working on be successful in pivotal or phase three clinical trials? Is the FDA going to approve it? Is there enough clinical utility that the payers will reimburse? Those are the three big things that determine whether a bio-pharmaceutical investment will be successful, and that's where the finance world really wants doctors…" Available at: http://www.leaddoc.org/Stories/2013/story1-0523.html#.Vyxg3vkrLIU [Accessed 16 August 2016]

liberal arts degrees are non-matching analysts. Analysts with irrelevant technological degrees, including non-chemical engineering degrees (such as electrical, civil, computer, geology and so on), are excluded from the sample as the effect of the irrelevant degrees on the chemical manufacturing industry analysis is unclear.

Being a financial analyst calls for a certain level of financial knowledge. Thus, matching analysts would normally undertake an MBA program or obtain a CFA (or CPA) certification to make up the lack of financial knowledge. Therefore, I assume that all the analysts, regardless of the types of degrees they hold, would be skilled with financial knowledge.[77] This may not be the case for non-matching analysts who only have a degree in business, literal arts, or social science. Unlike matching analysts doing an MBA or CFA for obtaining financial knowledge, non-matching analysts rarely do a second degree related to technology or natural science because they require a relevant technological background from the previous degree. Therefore, the financial knowledge of all analysts are levered. The technological knowledge is the additional expertise to analysts with a matching technological degree.

3.2.4 Hypotheses development

Analysts who have a matching technological degree are specialists in industries with great technological complexity. The technological knowledge from the degree would work best when it matches with the industry. Once analysts with technological degrees switch to another industry that has less technological complexity (such as the retail industry), or an unmatched industry, their technological degree may fall short. In contrast, business degrees are more likely to train analysts with knowledge related to management and financial analysis, which is transferrable knowledge across the industries when financial information is more relevant. Hence, analysts having a technological degree may cover less industries than their peers without a technological degree.

Hypothesis 1: analysts with a matching technological degree cover less industries than those with a non-matching degree.

[77] Section 4 will discuss the collection of analysts' educational background for the sample. All analysts identified have reported the source of financial knowledge they obtained (from either bachelor or master degree in a business related subject, or MBA, or CFA, or CPA). I do not see any analyst without financial knowledge.

Barth et al. (2001) find a positive association between analyst coverage and firms' R&D intensity, suggesting an overall benefit of covering a firm with great technological complexity. I argue that the cost of coverage may not be equal across analysts with different backgrounds. A matching technological degree that an analyst holds may mitigate the coverage cost more than a non-matching degree in that the matching degree would facilitate analysts to better analyze and process complex technological information. In contrast, analysts without a matching degree would bear higher cost on covering R&D-intensive firms relative to matching analysts. On this account, firms' R&D intensity may on one hand encourage analysts with a matching technological degree to cover them, and restrain, on the other hand, non-matching analysts from following them. Taken together, firms with great R&D intensity would be more likely to be followed by matching analysts than non-matching analysts, whereby my hypothesis is as follows:

Hypothesis 2a: Firms' analyst following by analysts with a matching (non-matching) degree is positively (negatively) associated with firms' R&D intensity.

Matching analysts may benefit from covering firms with great R&D intensity because they understand the technological knowledge better than non-matching analysts. However, matching analysts may not have such an advantage to cover firms with great complexity that are not primarily driven by R&D. In line with Barth et al. (2001), I use intangible assets on the balance sheet as the proxy of non-technological complexity, and expect that matching analyst following has no association with the amount of balance-sheet intangible assets.[78] Thus, my hypothesis is as follows:

Hypothesis 2b: The matching analyst following is not associated with the amount of firms' intangible assets on the balance sheet.

Amir et al. (2003) find that analysts' forecast error is positively associated with firms' R&D intensity, concluding that analysts fail to fully understand the impact of R&D on firms' future profitability. Likewise, Gu and Wang (2005) find that firms' information complexity of R&D increases the difficulty of information process, leading to an increase in analysts' forecast error. Further to this, I argue that a matching technological degree would assist analysts in processing complicated R&D

[78] I do not use advertising expense as over seventy percent of the advertising expense in my sample is missing.

information, resulting in a mitigation in the negative effect of firms' R&D intensity on forecast accuracy. In contrast, the matching degree would have less impact on the forecast accuracy influenced by the non-technological complexity, which is proxied by balance-sheet intangible assets. I use analysts' forecast error to be the proxy of forecast accuracy, whereby a larger forecast error suggests lower forecast accuracy. My hypothesis is as follows:

Hypothesis 3a: analysts' matching degrees mitigate the positive association between analysts' forecast error and firms' R&D intensity;

Hypothesis 3b: analysts' matching degrees do not mitigate the positive association between analysts' forecast error and the amount of firms' intangible assets on the balance sheet;

Next, I compare the market reaction to matching analysts' recommendation revisions to those of non-matching analysts. Frankel et al. (2006) argue that the primary role of financial analysts is to provide private information to their clients. Analysts collect and process public information, as well as generate and disseminate private information to the market, contributing to the price discovery process (Kim and Verrecchia 1997; Kim and Verrecchia 1994; Barron et al. 2002). Palmon and Yezegel (2012) find a positive association between the market reaction to analysts' recommendation revisions and the intensity of firms' R&D. They interpret the result as that firms with greater R&D are likely to be less informative in the stock prices. In this regard, analysts' activities would somewhat compensate for the weak information environment of R&D-intensive firms, and evoke a greater market reaction than R&D-free firms. In light of the difficulty in interpreting the complicated technological information, an analyst's ability to process such information may determine the quality of the private information she generates. I contend that analysts with a matching degree may be more competent in interpreting and processing complex technological information, and then generating more private information to the market compared to their peers without a matching degree. In alternative form, my fourth hypothesis is:

Hypothesis 4: The market reaction to the recommendations revised by analysts with a matching degree is greater than that by analysts without a matching degree.

Lastly, I compare analysts' boldness on the forecasts revised by matching analysts and by non-matching analysts. The extant literature in the analyst boldness area primarily pertains to analysts' characteristics, such as analysts' reputation (Scharfstein and Stein 1990); career concern (Hong et al. 2000; Hong and Kubik 2003); self-assessment ability (Trueman 1994); decision fatigue (Hirshleifer et al. 2017); and historical accuracy, forecasting frequency, general experience, as well as the number of industries that analysts cover (Clement and Tse 2005). Less research studies the association between analysts' boldness and firms' attributes. In one of the handful of studies, Lin et al. (2011) find that analysts are more likely to follow consensus recommendations (less bold) for larger firms and firms with higher book-to-market ratios. Leece and White (2017) study how the opacity of firms' information environment influences analysts' herding behavior. They use firms' transient institutional ownership as a measure of firms' information environment opacity, and find analysts tend to herd (issue less bold forecasts) in firms with greater opaque information environment where private information is more valuable than public information. In line with their argument, I argue that firms' R&D intensity may lead analysts to herd in that the technological complexity intensifies firms' information asymmetry (Aboody and Lev 2000). Compared to corporate insiders, sell-side analysts as a whole are a less informed party with less private information. On this account, analysts, on average, following R&D intensive firms are less likely to issue bold forecasts.

Hypothesis 5a: Analysts' boldness is negatively associated with firms' R&D intensity.

However, some analysts' personal traits may affect the negative association between analysts' boldness and firms' R&D intensity. Zwiebel (1995) develops a model to show an alternative herding incentive. An agent with average ability prefers conservativeness to innovations because innovations may lead to a greater downside risk of getting fired, while agents with high or low ability prefer innovations that involve more risk. Building on this, Hong, Kubik, and Solomon (2000) find that experienced analysts are more likely to issue bold forecasts than inexperienced analysts. In this paper, I argue that analysts with a matching degree would have high ability to collect and process information related to techological complexity, and subsequently issue forecasts that "stand out" from the consensus, relative to their peers without a matching degree. My hypothesis is as follows:

Hypothesis 5b: analysts' matching degree mitigates the negative association between firms' R&D intensity and boldness of analysts' forecasts

3.3 Research Design

3.3.1 Analysts' industry following

I use the Ordinary Least Square (OLS) regression to test Hypothesis 1. In an attempt to obtain more variations on the dependent variable, I use four-digit SIC to define industries. Then the number of four-digit SIC industries covered by each analyst is the dependent variable (*NUMIND*). The variable of interest is the indicator variable – $MATCH_j$, with the value of one if the analyst *j* has a matching technological degree, and zero for analysts without any technological degree. I exclude analysts with a technological degree that is irrelevant to chemical technology. In the model (1), I include several control variables: (1) the number of firms (*NUMCOM*) covered by each analyst within a year as the likelihood of an analyst following more industries may increase with the number of firms she covers; (2) the total number of forecasts made by each analyst within a year in the natural logarithm form (*lnNFORE_T*); (3) analysts' score of the forecast accuracy in the previous year in the natural logarithm form (*lnPACY*) in line with Hong and Kubik (2003); (4) analysts general experience (*lnGEXP*), defined as the natural logarithm form of the number of years since the analyst provided her first analyst forecast; and (5) the size of the brokerage house where the analyst works (*lnBRO*), measured as the number of analysts employed in the brokerage house in the natural logarithm form. I also include year fixed effect and/or brokerage house fixed effect in the various specifications. When the brokerage house fixed effect is included, I drop *lnBRO* to avoid the perfect multicollinearity. I double cluster standard errors at the analyst and year levels to correct for cross-sectional and time-series dependence.

$$\begin{aligned} NUMIND_{jt} = \alpha_0 &+ \alpha_1 MATCH_j + \alpha_2 NUMCOM_{jt} \\ &+ \alpha_3 lnNUMFOR\_TOT_{jt} + \alpha_4 lnPACY_{jt} \\ &+ \alpha_5 lnGEXP_{jt} + \alpha_6 lnBRO_{jt} + \varepsilon_{jt} \end{aligned} \tag{3.7}$$

3.3.2 Firms' analyst coverage

Turning to the test of firms' analyst coverage, I build on the research design builds upon Barth et al. (2001). Specifically, I examine the association between the matching analyst following and firms' R&D intensity. Thus, the dependent variable is the number of analysts that have a matching degree (*AF_MA*). As a comparison, I also replicate the regression with total analyst following (*AF_TOT*) and the non-matching analyst following (*AF_nonMA*). The variable of interest is annual R&D expense scaled by total operating expense (*RD*). [79] In order to control the effect of intangible assets on the analyst coverage decision, I include balance-sheet intangible assets (*INTA*) as one of the explanatory variables, defined as intangible assets on the balance sheet scaled by total assets. In line with Barth et al. (2001), I include the average analyst effort for covering a firm (*EFF*), defined as the sum of firms followed by a firm's all analysts scaled by the number of analyst following the firm, multiplying by -1. Other control variables are the market value of equity in the natural logarithm form (*lnMCAP*), stock return volatility (*RETVOL*), the percentage of institutional investor ownership (*INST*), the correlation between the stock return and the market return (*RSQ*), the market-to-book ratio (*BM*) (Bhushan 1989; O'Brien and Bhushan 1990; Lang and Lundholm 1996; Frankel et al. 2006). In line with the Barth et al. (2001), I also control for the industry-year level variations by adding four-digit SIC industry times year fixed effect.[80] I double cluster standard errors at the firm and year levels. The model is shown as follows:

$$\begin{aligned} AF_{it} = \alpha_0 + \alpha_1 RD_{it} + \alpha_2 INTA_{it} + \alpha_3 lnMCAP_{it} + \alpha_4 RETVOL_{it} \\ + \alpha_5 RSQ_{it} + \alpha_6 INST_{it} + \alpha_7 BM_{it} + IndustryYear\ FE \\ + \varepsilon_{it} \end{aligned} \qquad (3.8)$$

where *AF* is *AF_MA*, *AF_TOT*, and *AF_nonMA*, in each specification.

3.3.3 Analysts' forecast accuracy

This section examines the impact of matching analysts on the negative association between analysts' forecast accuracy and firms' R&D documented in the previous literature. The dependent variable is forecast error (*FORERROR*), defined as the absolute value of the difference between the one-year-ahead annual EPS forecast and the actual EPS value, and scaled by the stock price two days before the forecast is made. Thus greater forecast error suggests lower forecast accuracy. I create an

[79] Some research chooses total sales as the deflator. I keep in line with Barth et al. (2001) who use total operating expense as the deflator. In the chemical manufacturing industry, especially pharmaceutical companies, the R&D expenditure is enormous before it generates any revenue. Switching to sales as the deflator will generate many extreme observations in the sample.

[80] In Barth et al. (2001), the authors calculate the industry-year median of R&D and balance-sheet intangible assets for each firm, and add them back to the model as the additional control variable. In my paper, I use industry times year fixed effect.

indicator variable – *MATCH* equal to one for matching analysts and zero for non-matching analysts, and interact it with *RD*.[81] Then the interactive term *MATCH* × *RD* captures the influence of the matching degree on the association between analysts' forecast error and firms' R&D intensity. In addition, I also include balance-sheet intangible assets (*INTA*) and the interaction term with the matching indicator – *MATCH* × *INTA* – in the model to investigate whether the matching degree also has an impact on the forecast error related to the non-technological complexity. I include a set of analyst-related and firm-related control variables documented in the prior literature: analysts' firm-specific experience (*lnFEXP*) defined as the number of years in the natural logarithm form since the analyst provided her first forecast for the firm, and general experience (*lnGEXP*) defined as in the previous section (Clement 1999; Mikhail et al. 1997); the numbers of firms and industries that the analyst covers in the natural logarithm form (*lnNUMCOM* and *lnNUMIND*) (Clement 1999); the size of the brokerage house (*lnBRO*) and the score of analysts' past forecast accuracy (*lnPACY*) as defined previously; as well as the forecast horizon measured as the number of days, in the natural logarithm form, from when the forecast is provided to when the firm's earnings is released (*lnHOR*). Firm-related control variables are the market value of equity (*lnMCAP*), total analyst following in the natural logarithm form (*lnAF*), the percentage of institutional investor ownership (*INST*), the market-to-book ratio (*BM*), and stock return volatility (*RETVOL*), and a dummy variable for the firm with a negative net income (Hwang et al. 1996; Brown 2001). In addition, I include four-digit SIC industry times year fixed effects. I double cluster standard errors at the analyst and the year levels.

$$\begin{aligned} FORERR_{ijt} = {} & \alpha_0 + \alpha_1 RD_{it} + \alpha_2 INTA_{it} + \alpha_3 MATCH_j + \alpha_4 MATCH_j \\ & \times RD_{it} + \alpha_5 MATCH_j \times INTA_{it} + \boldsymbol{\beta CONTROL} \\ & + IndustryYear\ FE + \varepsilon_{ijt} \end{aligned} \tag{3.9}$$

3.3.4 Market reactions to the recommendation revisions

This section details the research design to examine the market reaction to the recommendations revised by the matching analysts relative to non-matching analysts. I use 5-day cumulative abnormal CRSP value-weighted adjusted returns ([-1, +3]-day)

[81] Consistent with the research design for the Hypothesis 1, I exclude analysts with technological degrees irrelevant to the chemical manufacturing industry.

as the measure of the market reaction (*CAR*). Palmon and Yezegel (2012) find a positive association between the cumulative abnormal return around analysts' recommendation revisions and firms' R&D intensity. I argue that market reactions to the recommendations revised by matching analysts are greater than non-matching analysts. In line with Palmon and Yezegel (2012), I classify revisions as upward (downward) revisions if the current recommendation is more (less) favorable than the previous one that are also provided by the same analyst, and delete all reiterated revisions. I firstly test no-directional revisions where I multiply cumulative abnormal returns for downward revisions by -1. I also run the regression in the subsamples with upward revisions and downward revisions separately. The variables of interest are still *MATCH*, *RD*, and their interaction term. I control for firm size (*lnMCAP*), the book-to-market ratio (*BM*), institutional investor ownership (*INST*), total analyst following (*lnAF*), and stock return volatility in the percentage form (*RETVOL_PC*). Analyst-related control variables are analysts' firm-specific experience (*lnFEXP*), general experience (*lnGEXP*), the numbers of firms and industries covered (*lnNUMCOM* and *lnNUMIND*), and analysts' past forecast accuracy (*lnPACY*). Additionally, Industry times year fixed effect are also included. All variables are previously defined. I adjust standard errors for two-way clustering at the firm and year levels. Then the model is as follows:

$$CAR_{ijt} = \alpha_0 + \alpha_1 RD_{it} + \alpha_2 MATCH_j + \alpha_3 MATCH_j \times RD_{it} + \boldsymbol{\beta CONTROL} + IndustryYear\ FE + \varepsilon_{ijt} \quad (3.10)$$

3.3.5 Boldness

This section provides the research design to test the boldness between matching analysts and non-matching analysts. Following Clement and Tse (2005), I define the dependent variable, $BOLD_{ijt}$, as an indicator variable, equal to one if analyst j's forecast is above both her prior forecast and the consensus forecast immediately before her forecast revision, or else below both. It is set to zero otherwise. The consensus forecast is calculated as the mean of forecasts issued by all analysts within 90 days prior to analyst j's forecast. The variables of interest are all previously defined, which are *MATCH*, *RD*, and their interaction term. Firm-related control variables are *lnMCAP*, *BM*, *INST*, *lnAF*, and *RETVOL*. Analyst-related variables are *lnFEXP*, *lnGEXP*, *lnNUMCOM*, *lnNUMIND*, *lnNFORE_T*, *lnNFORE_F*, *lnPACY*, and *lnHOR*. Besides, I also control the days elapsed (*lnELAPSE*), as suggested in Clement and Tse

(2005), which is defined as the number of days since the last forecast made by each analyst following the firm within the year in the natural logarithm form. I use a logistic model to run the regression with industry times year fixed effects. I cluster the standard error by analysts. The model is as follows:

$$\begin{aligned} Pr(BOLD_{ijt} = 1) \\ &= \alpha_0 + \alpha_1 RD_{it} + \alpha_2 MATCH_j + \alpha_3 MATCH_j \times RD_{it} \\ &+ \boldsymbol{\beta CONTROL} + IndustryYear\ FE + \varepsilon_{ijt} \end{aligned} \quad (3.11)$$

3.4 Data and sample

3.4.1 Data collection

The key variable in this paper is analysts' educational background. In order to identify the biographical information of analysts who cover the chemical manufacturing industry, I firstly merge the recommendation file in the Institutional Broker Estimate System (*I/B/E/S*) with *CRSP/Compustat Merged* (*CCM*). I/B/E/S provides analysts' surnames, initials of their first names, and their employment history. CCM provides SIC codes. I keep firms in the chemical manufacturing industry only (SIC 2800 to 2899) for the period from 2003 to 2016. Then I obtain 1,118 firms and 2,028 analyst codes to be identified (Table 3.1, Panel A). Next, I search analysts' surnames, initials of first names, and their brokerage houses on Bloomberg, and manually match analysts' coverage portfolio in I/B/E/S and the coverage list of analysts in Bloomberg who have the same surname, first-name initial and the brokerage house.[82] Once matched successfully, I have the full name. Lastly, by using the full names identified in the previous step, together with the name of their employing brokerage houses, I go to *LinkedIn* and search those analysts' names for their educational background (Bradley et al. 2017). If analysts' full name and their employing brokerage houses from *LinkedIn* are matched with that from Bloomberg, the biographical identification is successful. Using this technique, I obtained the majority of analysts' educational information from *LinkedIn*. In some cases when *LinkedIn* fails to provide the analyst's degree or specify the major of the degree, I go

[82] This step is essential in the identifying process. As I only have partial information of analysts' name, Bloomberg returns multiple results quite often when I use surnames and first-name initials only, especially for those widely-used surnames like "Brown", "Williams", or "Li" etc. Bloomberg provides analysts' coverage list, which presents the names of the firms they follow. Matching the coverage lists from Bloomberg and I/B/E/S would to the largest extent reduce mistakes in the process of identification.

for alternative sources, such as the official websites of the brokerage houses, some search engines that specialize in collecting biographical information like *zoominfo.com* (Cohen et al. 2010), and other websites that also provide some analysts' information such as *streetwisereoports.com* and *twst.com.*

Other variables are collected from various sources. I obtain accounting fundamental variables from *CCM*, analyst-related variables from *I/B/E/S*, stock price from *CRSP*, ownership of institutional investors from *Thomson Reuters*, and the *CRSP* value-weighted cumulative abnormal return from *EventStudy by WRDS*.

3.4.2 Sample description

Panel (A) of Table 3.1 reports the result of the analyst identification. Starting with 2,028 identifiable analysts' codes, I successfully identified 1,218 US analysts with their complete educational information, and 391 non-US analysts, which together account for nearly eighty percent of total identifiable codes (Panel B). I keep US analysts only in an attempt to mitigate the geographical influence on analysts' performance (Malloy 2005; Bae et al. 2008). Panel (C) presents the result of analysts' classification by the type of their degrees. By reading the title of all identified analysts' degrees, I find that 440 analysts have a matching technological degree, accounting for 36%; as well as 703 non-matching analysts that only have business, literary arts, or social science related degrees, accounting for 58%. The remaining 75 analysts have irrelevant technological degrees, which are excluded from the analysis. Panel (D) and Panel (E) of Table 3.1 report the numbers of matching and non-matching analysts by four-digit SIC and by year respectively. Specifically, in Panel (D), the first two columns show that the chemical manufacturing industry is dominated by firms with an SIC of 2834, 2835 or 2836. These firms, together with firms in 2833, are medical, pharmaceutical, or biological product manufacturers (Appendix 1 reports the names of industries in detail).[83] All firms with a SIC starting with 283 account for over eighty percent of the total number of chemical manufacturing companies and are followed by a great portion of analysts with a matching degree. Turning to Panel (E), the total number of analysts covering the chemical manufacturing industry is stable during the

[83] Firms in 2833 manufacture medicinal chemicals and botanical products. Firms in 2834 manufacture pharmaceutical preparations. Firms in 2835 manufacture in vitro and in vivo diagnostic substances. Firms in 2836 manufacture biological products.

sample period. In a similar vein, the number of matching analysts does not have a large variation either, ranging from 39.4% in 2014 to 46.5% in 2005.

3.5 Empirical results

3.5.1 Analysts' industry coverage

In this section I present the result for Hypothesis 1 – analysts with a matching technological degree cover less industries than those with a non-matching degree. The unit of analysis is analyst-year. Table 3.2, Panel (A) shows the descriptive statistics for matching analysts and non-matching analysts respectively. Compared to non-matching analysts, matching analysts on average follow less industries and have less general experience. However, they do not have much difference regarding the number of firms in their coverage portfolio (*NUMCOM*), the annual forecasting frequency (*lnNFORE_T*), their past forecast accuracy (*lnPACY*), or the size of employing brokerage house (*lnBRO*). Panel (C) reports the results in different specifications. Consistent with my hypothesis, the *MATCH* coefficient is negatively significant in all specifications, indicating that analysts with a matching technological degree are less likely to cover multiple industries that are not relevant to their educational degrees. With regard to control variables, the coefficient on the number of firms that each analyst follows (*NUMCOM*) is significantly positive, suggesting a positive association between the number of industries and the number of firms covered by an analyst. The size of the employing brokerage house reports a negative coefficient, meaning that analysts from large brokerage houses cover less industries, which may be ascribed to their colleagues sharing the workload. In sum, the result supports Hypothesis 1 that analysts with a matching technological degree follow less industries than their peers without a matching degree.

3.5.2 Firms' analyst following

In this section, I present the results for Hypothesis 2 – the association between firms' matching (non-matching) analyst following and the R&D intensity. The unit of analysis is firm-year. Panel (A) of Table 3.3 reports the statistical description of the data. On average, one firm is followed by 6.41 analysts (*AF_TOT*), of which 2.86 analysts have a matching degree (*AF_MA*) and 1.90 analysts have non-matching degrees (*AF_nonMA*).[84] The mean of *RD* is 0.36, indicating that firms' R&D expense on average amounts to 36% of the total operating expense. Intangible assets (*INTA*) is highly right skewed with a mean of 0.13 and a median of 0.04, which suggests most firms have few intangible assets or fail to report intangible assets on the balance sheet.

Panel (C) of Table 3.3 reports the regression results with different dependent variables in each specification. In model (i) where the total number of analyst following (*AF_TOT*) is the dependent variable, I find that the estimated coefficient on *RD* is positively significant, which is consistent with Barth et al. (2001), indicating that the net benefit of covering R&D-intensive firms is positive. In addition, the coefficient on the intangible assets is insignificant, whereas Barth et al. (2001) find a negatively significant result that contradicts their hypothesis. Next, I partition *AF_TOT* into matching analyst following (*AF_MA*) and non-matching analyst following (*AF_nonMA*) and re-run the regression.[85] Model (ii) uses matching analyst following as the dependent variable. The estimated coefficient on *RD* is still positively significant and the magnitude is larger than that in model (i). Turning to model (iii) where the dependent variable is non-matching analyst following (*AF_nonMA*), the result changes drastically. The estimated coefficient on *RD* is significantly negative, suggesting that analysts without a matching technological degree are less likely to follow firms with greater R&D. Moreover, the *INTA* coefficient turns positively significant, indicating a positive association between non-matching analyst following and intangible assets on the balance sheet. With regard to the control variables, most of them are consistent with prior literature. I find that analyst following is positively associated with the market value of equity, the stock return volatility, and intuitional investors' ownership (Bhushan 1989; O'Brien and Bhushan 1990). Moreover, the negative coefficient on *EFF* suggests that analysts are reluctant to cover firms requiring great effort to follow. Collectively, I find the evidence consistent with Hypotheses 2a and 2b that the cost of covering R&D intensive firms is lower for matching analysts than non-matching analysts, evidenced by a positive (negative) association between the firm's R&D intensity and matching (non-matching) analyst following.

[84] The means of *AF_MA* and *AF_nonMA* do not add up to *AF_TOT*, because *AF_TOT* includes non-US analysts, irrelevant-degree analysts, and unidentified analysts.

[85] As I delete non-US analysts, analysts with irrelevant technology-related degrees, and unidentified analysts, so that the sum of coefficients in Model (ii) and Model (iii) does not equal that in Model (i).

3.5.3 Analyst forecast accuracy

This section presents the result for testing analysts' forecast accuracy. I use forecast error as the proxy of forecast accuracy. Then larger forecast error indicates lower forecast accuracy. I run the regression (3.3) in one full sample and two sub-samples. In an attempt to balance the forecasting frequency of analysts for different firms, the first sub-sample only contains the last annual earnings forecast made by each analyst for each firm within a year (De Franco and Zhou 2009). The second sub-sample contains earnings forecasts provided within the week following firms' quarter or annual earnings announcement. The earnings announcement discloses a large amount of information. The second subsample may lever the cost of information collection so that the test would mainly reflect analysts' ability to process the information. For the purpose of simplicity, I report data description and correlation matrix for the full sample only.

Panel (A) of Table 3.4 reports summary statistics for matching and non-matching analysts separately. Analysts with a matching degree have a higher level of forecast error compared to non-matching analysts. This counter-intuitive result could be justified by the higher R&D amount in the matching analyst group in the sense that matching analysts mainly cover R&D-intensive firms that are hard to forecast.[86] Moreover, more than half of firms followed by matching analysts have negative earnings in the previous year, whereas this figure in the non-matching analyst group is only 27%, which may also explain the higher forecast error in the matching group. Furthermore, non-matching analysts cover more industries than matching analysts, which is in line with Hypothesis 1 that matching analysts are specialists and more likely to only cover the industry matching their technological knowledge. The statistics for the remaining variables are similar between the two groups.

Panel (C) of Table 3.4 presents the regression results. Columns (i) and (ii) report the results for the full sample. Columns (iii) and (iv) are for the sub-sample with the last observation within a year, and columns (v) and (vi) are for the sub-sample with the observations in the week following the earnings announcement. Column (i) shows that R&D is positively associated with analysts' forecast error, consistent with Gu and Wang (2005) and Amir et al. (2003). However, the *INTA* coefficient is insignificant at

[86] This is consistent with Hypothesis 2 in this paper.

any conventional level. Turning to column (ii) where I introduce the interaction terms of dummy variable *MATCH* with *RD* and with *INTA*, the coefficient on *RD* represents the effect of R&D intensity on the error of forecasts made by non-matching analysts. The estimated coefficient is 0.847, implying that a one-standard-deviation increase in *RD* is associated with 0.21 increase in forecast error from non-matching analysts, which amounts to 16% of the mean of forecast error.[87] The coefficient on the interaction term is -0.430, indicating analysts with a matching degree mitigate the impact of R&D on forecast error by 0.430 (or 51% relative to non-matching analysts). The overall impact of R&D on matching analysts is 0.417 (as in 0.847-0.430), suggesting a one-standard-deviation increase in *RD* is only associated with 0.117 increase in forecast error among matching analysts, which amounts to 6.2% of the mean of forecast error.[88] The R&D results in the two subsamples are similar to that in the full sample, albeit one insignificant coefficient on the R&D in column (iii). Turning to balance-sheet intangible assets, the results support the Hypothesis 3b. The interaction term of R&D and intangibles report different results in different samples. In column (iv), the positively significant coefficient on the interaction term suggests analysts with a matching degree perform worse with an increase in the balance-sheet intangible assets. However, the result is insignificant in columns (ii) and (vi) where different samples are chosen. Collectively, consistent with Hypothesis 3a, I find that firms' R&D has an unfavorable impact on analysts' forecasting error, probably due to the technological complexity generated by R&D. The technological degree that matching analysts possess significantly mitigates such impact. Furthermore, the matching degree does not mitigate the unfavorable effect on the analyst forecasts ascribed to balance-sheet intangible assets.

3.5.4 The market reaction to recommendation revisions

This section reports the results for Hypothesis 4. I run the regression with three different samples based on the direction of the recommendation revisions. In the first sample, I multiply the dependent variable, 5-day *CAR*, for downward revisions by -1

[87] The standard deviation and the mean of the forecast error in the non-matching group are 0.25 and 1.32 respectively. Therefore, one-standard-deviation increase in *RD* affects forecast error by 0.847 × 0.25, which is 0.21. I compare this figure to the mean, 0.21/1.32, and obtain 16%

[88] The standard deviation and the mean of the forecast error in the matching group are 0.28 and 1.90 respectively. Therefore, one-standard-deviation increase in *RD* affects forecast error by 0.417 × 0.28, which is 0.117. I compare this figure to the mean, 0.117/1.90, and obtain 6.2%.

to account for the different signs of *CAR* to the upward and the downward revisions. Then I obtain a uniform measure of market reactions with all the observations. Next, I run the regressions in two subsamples that only contain upward or downward revisions respectively. Panel (A) in Table 3.5 shows the data description with different samples. The *CAR* in the non-direction sample has a mean of 5.75 basis points. This figure in the upward-revision sample is 4.05 basis points and -6.61 basis points in the downward-revision sample.

In Panel (C), columns (i), (iii), and (v) report the results of regressions without the interaction term. I find a positive association between the R&D intensity and the market reaction when analysts issue upward recommendation revisions. In addition, the *MATCH* coefficient is also positively significant in the specification when upward recommendations are provided, which suggest that investors value analysts' matching technological degrees, in particular when analysts provide favorable recommendations. Turning to models where the interaction term of R&D with matching degree is included, the result in column (iv) reports a significant positive coefficient, indicating that the positive association between the market reaction and R&D intensity is more pronounced on the recommendations revised by the analysts with a matching degree than non-matching analysts, when recommendations are favorable. However, when it comes to downgrades as shown in columns (v) and (vi). I fail to find any significance on the interaction term or the main variable at any conventional level. Overall, I find evidence that supports the Hypothesis 4 that the association between the market reaction to analysts' recommendation and firms' R&D intensity is more pronounced among matching analysts than non-matching analysts. However, the evidence only holds for the favorable recommendation revisions.

3.5.5 Boldness

In this section, I present the results for the test of analysts' boldness in Table 3.6. In line with the concern in testing analysts' forecast error, I run the logistic regressions with three different samples: (1) the full sample; (2) the sub-sample with the last observation of the forecast made by each analyst within each year; and (3) the sub-sample that contains forecasts made in the week following earnings announcement. Firstly, I find the result consistent with my hypothesis within the full sample in models (i) and (ii). The negatively significant coefficient on *RD* indicates that analysts' boldness is negatively associated with firms' R&D intensity, while the positively significant coefficient on the interaction term *MATCH* × *RD* suggests that analysts matching degree alleviates such negative impact. When switching to sub-samples, I still find consistent results for Hypothesis 5a in terms of the association between analysts' boldness and R&D intensity, presented in models (iii) to (vi). However, I fail to find evidence for Hypothesis 5b as the estimated coefficients on the interaction term *MATCH* × *RD* are insignificant at any conventional levels.

As the entire sample contains over eighty percent pharmaceutical firms (SIC 2833 to 2836) who have more R&D than non-pharmaceutical firms in general, the test power may be stronger within the pharmaceutical firms than non-pharmaceutical firms. In this regard, I restrict the sample and replicate the regression (3.5) with pharmaceutical firms (labeled as "Pharma firms") only. Then I find the results consistent with my hypotheses across all specifications. Panel (D) reports the empirical results. In models (i), (iii), and (v), the *RD* coefficient is significantly negative in all specifications, consistent with Hypothesis 5a that analysts' boldness is negatively associated with firms' R&D intensity. When including *MATCH*, and the interaction term *MATCH* × *RD* in models (ii), (iv), and (vi), as predicted in the Hypothesis 5b, the interaction term exhibits a significantly positive coefficient in all models, indicating that the matching degree mitigates the negative influence of R&D intensity on analysts' boldness. Collectively, I find the evidence to support Hypothesis 5a and 5b in the restricted sample that contains pharmaceutical firms only.

3.6 Conclusion

The extant literature has documented analyst-related and firm-related factors that have an impact upon analysts' coverage decision and forecasting behavior. This paper focuses on the interactive effect of these two forces. More precisely, I explore the impact of analysts' technology-related knowledge and firms' technological complexity. I focus on the chemical manufacturing industry, and use firms' R&D intensity to measure the degree of technological complexity relative to their industry peers, as well as analysts' educational degree as a proxy of their technological knowledge to test whether a matching educational degree alleviates the negative impact of firms' R&D on analysts' behavior. Based on the analysis above, I have following findings. Firstly, I find analysts with a matching degree cover less industries. Secondly, extending the finding in Barth et al. (2001), I find that firms'

R&D intensity is positively (negatively) associated with analyst following of analysts that (do not) have a matching technological degree. Furthermore, I find that analysts' matching degree mitigates the negative impact between firms' R&D intensity and analysts' forecast accuracy. Next, I find that analysts with a matching degree elicit a greater market reaction to recommendation revisions when firms have a high level of R&D intensity. However, the result only holds for the upward revisions. Finally, I find that firms' R&D intensity negatively affects analysts' boldness, but analysts' matching degree alleviates this negative influence within the restricted sample that only contains pharmaceutical firms.

This paper has the following caveats. Firstly, I focus on one industry only. Thus, generalization to other industries may be a concern, especially for the industries that demand less technological knowledge such as retail, wholesale or services industries. Secondly, I do not have a clear setting to draw a causal inference of the interactive effect between these two forces on analysts' behavior, which calls for further research to identify an exogenous shock to the industry.

3.7 Appendix: The name of each 4-digit SIC industries.

This table lists the name of each four-digit SIC industries from U.S. Securities and Exchange Commission (SEC) official website: https://www.sec.gov/info/edgar/siccodes.htm

SIC	Name
2800	Chemicals & allied products
2810	Industrial inorganic chemicals
2820	Plastic material, synth resin/rubber, cellulose (no glass)
2821	Plastic materials, synth resins & non-Vulcan elastomers
2833	Medicinal chemicals & botanical products
2834	Pharmaceutical preparations
2835	In vitro & in vivo diagnostic substances
2836	Biological products, (no diagnostic substances)
2840	Soap, detergents, cleaning preparations, perfumes, cosmetics
2842	Specialty cleaning, polishing and sanitation preparations
2844	Perfumes, cosmetics & other toilet preparations
2851	Paints, varnishes, lacquers, enamels & allied prods
2860	Industrial organic chemicals
2870	Agricultural chemicals
2890	Miscellaneous chemical products
2891	Adhesives & sealants

3.8 Appendix: Definition of variables

Firm-level variables		
Variable Name	Description	Source
AF_MA	The number of analysts having a matching technological degree following each firm.	I/B/E/S
AF_nonMA	The number of analysts not having a matching technological degree following each firm. Irrelevant degrees such as industrial engineering are not included.	I/B/E/S
AF_TOT	Total number of analysts following each firm, regardless of their educational degrees.	I/B/E/S
BM	Book value of equity divided by market value of equity.	Compustat
CAR_UP	5-day [-1, 3] cumulative abnormal CRSP value-weighted adjusted returns, in the percentage form, to upward recommendation revisions.	EventStudy by WRDS
CAR_DOWN	5-day [-1, 3] cumulative abnormal CRSP value-weighted adjusted returns, in the percentage form, to downward recommendation revisions.	EventStudy by WRDS
CAR_nonD	5-day [-1, 3] cumulative abnormal CRSP value-weighted adjusted returns, in the percentage form, to all recommendation revisions, adjusting the downward reaction by multiplying -1.	EventStudy by WRDS
EARNANN	Dummy variable, set equal to one on the day when a firm announces the earnings, and zero otherwise.	I/B/E/S
EFF	Firms' average analyst effort, calculated as the sum of the number of firms followed by all analysts for a firm divided by the number of analysts following the firm within a year, then multiple by -1.	I/B/E/S
INTA	Intangible assets scaled by total assets in the percentage form.	Compustat
LOSS	Dummy variable, set equal to one when actual EPS in the previous year is negative, and zero otherwise.	Compustat
lnMCAP	Market value of equity in the logarithm form.	Compustat
lnAF	Total analyst following in the logarithm form.	I/B/E/S
R_SQ	R-squared from the regression of daily stock return on the market return (the return of OMX30 index) within each year.	CRSP
RD	Annual R&D expense scaled by total annual operating expense.	Compustat
RETVOL	Standard deviation of the daily stock return within each year.	CRSP
RETVOL_PC	Standard deviation of the daily stock return within each year in the percentage form	CRSP

Analyst-level variables		
Variable Name	Description	Source
BOLD	Indicator variable, equal to one if an analyst's forecast is above both her prior forecast and the consensus forecast immediately before her forecast revision, or else below both. It is set to 0 otherwise. The consensus forecast is calculated as the mean of forecasts issued by all analysts within 90 days prior to the analyst's forecast.	I/B/E/S
FORERROR	Analyst forecast error. Take the absolute value of the difference between the one-year ahead EPS forecast and actual EPS, scaled by the stock price two days before the forecast is provided, then times 100.	I/B/E/S
lnBRO	The number of analysts employed in a brokerage house in the logarithm form.	I/B/E/S
lnELAPSE	The number of days since last forecast made by any analyst in the logarithm form.	I/B/E/S
lnFEXP	Firm-specific experience in the logarithm form. Firm-specific experience is measured as the number of days from the analyst's first opinion for the specific firm to the present.	I/B/E/S
lnGEXP	General experience in the logarithm form. Analyst general experience is measured as the number of days from the analyst's first opinion for any firm to the present.	I/B/E/S
lnHOR	Forecast horizon in the logarithm form. Forecast horizon is the number of days between the date when the forecast is provided and the date when the actual EPS is announced.	I/B/E/S
lnNUMCOM	Total number of firms covered by an analyst in the logarithm form.	I/B/E/S
lnNFORE_F	Total number of forecasts provided by an analyst for a firm within a year in the logarithm form.	I/B/E/S
lnNFORE_T	Total number of forecasts provided by an analyst for any firm within a year in the logarithm form.	I/B/E/S
lnNUMIND	Total number of industries (four-digit SIC codes) covered by an analyst in the logarithm form.	I/B/E/S
lnPACY	Analysts' relative accuracy score in the previous year in the logarithm form. Analyst's relative accuracy score is calculated in line with the method in Hong and Kubik (2003).	I/B/E/S
MATCH	Indicator variable, equals one if an analyst has a matching degree, and zero otherwise.	Bloomberg and LinkedIn
NUMCOM	Total number of firms covered by an analysts.	I/B/E/S
NUMIND	Total number of industries (four-digit SIC codes) covered by an analyst.	I/B/E/S

Table 3.1: Data collection and general description of the sample

This table presents the result of the identification of analysts' educational degrees within the sample period from 2003 to 2016. Panels (A), (B), and (C) show the source of data, the successful rate of identification, and the numbers of matching, non-matching, and irrelevant analysts respectively. Panel (D) and Panel (E) report the numbers of matching and non-matching analysts by four-digit-SIC industries and by years respectively.

Panel (A): Analysts' identification

	No.	Source
Firms in the chemical manufacturing industry	1,118	COMPUSTAT
Codes of analysts in Recommendation file	45,684	I/B/E/S
Codes of analysts covering chemical manufacturing industry	2,028	COMPUSTAT and I/B/E/S

Panel (B): Analysts' educational degree identification

Analysts identifying	No.	Percent
Fully identified	1,218	60.1%
Non-US analysts	391	19.3%
Degree title not specified	98	4.8%
No university information	92	4.5%
Unidentified	52	2.6%
I/B/E/S error 1: same name, different codes	69	3.4%
I/B/E/S error 2: same code, different names	108	5.3%
Total	2,028	100.0%

Panel (C): Number of analysts have a matching degree or non-matching degree

	No.	Percent
Matching analysts	440	36.1%
Non-matching analysts	703	57.7%
Irrelevant technological degree	75	6.2%
Total	1,218	

Panel (D): Matching and non-matching analysts by four-digit SIC industries

Firms		Analysts					
SIC	No. of firms	Total No. of analysts	Total No. of identified US	No. of match	No. of non-match	No. of irrelevant	Match / Total identified%
2800	10	57	26	7	16	3	26.9%
2810	29	183	133	30	88	15	22.6%
2820	9	72	52	18	30	4	34.6%
2821	17	141	97	33	55	9	34.0%
2833	13	116	82	35	46	1	42.7%
2834	346	992	584	319	252	13	54.6%
2835	79	402	304	180	118	6	59.2%
2836	488	814	539	333	193	13	61.8%
2840	7	103	49	1	48	0	2.0%
2842	5	91	70	7	62	1	10.0%
2844	18	122	74	3	68	3	4.1%
2851	7	110	65	19	42	4	29.2%
2860	40	220	142	24	112	6	16.9%
2870	28	210	114	18	86	10	15.8%
2890	17	187	148	31	95	22	20.9%
2891	5	45	35	5	27	3	14.3%
Total	1,118						

Panel (E): Matching and non-matching analysts by years

Firms		Analysts					
Year	No. of firms	Total No. of analysts	Total No. of identified US	No. of match	No. of non-match	No. of irrelevant	Match / Total identified%
2003	482	491	284	116	152	16	40.8%
2004	512	531	322	141	162	19	43.8%
2005	521	565	342	159	163	20	46.5%
2006	534	579	373	165	182	26	44.2%
2007	529	581	380	168	188	24	44.2%
2008	484	589	404	173	206	25	42.8%
2009	444	535	370	156	188	26	42.2%
2010	431	572	400	160	217	23	40.0%
2011	419	552	386	163	206	17	42.2%
2012	417	525	376	153	204	19	40.7%
2013	468	522	361	148	199	14	41.0%
2014	565	554	388	153	219	16	39.4%
2015	620	561	395	162	217	16	41.0%
2016	614	578	403	163	225	15	40.4%

Table 3.2: Analysts' industry coverage

This table presents statistics and results for Hypothesis 1 – matching analysts cover less industries than non-matching analysts. Panel (A) presents descriptive statistics for variables used in the regression. The dependent variable (*NUMIND*) is the number of four-digit-SIC industries covered by each analyst. *MATCH* is an indicator variable, equals to one if the analyst has a matching technological degree, and zero otherwise. *NUMCOM* denotes the number of firms followed by each analyst within each year. *lnNFORE_T* is defined as the number of forecasts provided by an analyst within the year in the logarithm form. *lnPACY* denotes the relative accuracy score of an analyst in the previous year in the logarithm form, which is calculated in line with Hong and Kubik (2003). *lnGEXP* is analysts' general experience in the logarithm form, measured as the number of years from when the analyst provides her first forecast for any firms to present. *lnBRO* is the size of the employing brokerage house in the logarithm form, calculated as the number of analysts within each brokerage house within each year. Panel (B) reports Pearson (below diagonal) and Spearman (above diagonal) correlations. The correlations significant at the five percent level are shown in bold. Panel (C) outlines the results. Standard error is clustered at the analyst and the year levels. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

MATCH=1								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
NUMIND	1,937	4.22	2.83	1	2	3	6	18
NUMCOM	1,937	14.65	7.15	1	10	14	19	37
lnNFORE_T	1,937	3.78	0.92	0	3.47	4.03	4.36	5.2
lnPACY	1,937	3.91	0.31	1.77	3.81	3.96	4.09	4.50
lnGEXP	1,937	1.86	0.97	0	1.1	1.95	2.64	3.47
lnBRO	1,937	3.57	1.13	0	2.77	3.66	4.52	5.63

MATCH=0								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
NUMIND	4,659	6.69	3.98	1	4	6	9	18
NUMCOM	4,659	15.46	7.43	1	11	15	20	37
lnNFORE_T	4,659	3.87	0.91	0	4	4	4	5
lnPACY	4,659	3.9	0.31	0.01	3.79	3.94	4.07	4.50
lnGEXP	4,659	2.21	0.99	0	1.61	2.48	3.04	3.47
lnBRO	4,659	3.56	1.16	0	2.83	3.64	4.51	5.63

Panel (B): Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	*NUMIND*		**-0.31**	**0.52**	**0.42**	-0.02	**0.19**	**-0.06**
(2)	*MATCH*	**-0.29**		**-0.05**	**-0.06**	**0.04**	**-0.18**	0.00
(3)	*NUMCOM*	**0.54**	**-0.05**		**0.83**	**0.03**	**0.27**	**0.12**
(4)	*lnNFORE_T*	**0.43**	**-0.05**	**0.78**		**0.08**	**0.25**	**0.21**
(5)	*lnPACY*	**0.03**	0.02	**0.10**	**0.17**		-0.01	**0.07**
(6)	*lnGEXP*	**0.19**	**-0.16**	**0.27**	**0.23**	**0.04**		**0.03**
(7)	*lnBRO*	**-0.06**	0.00	**0.11**	**0.19**	**0.09**	0.02	

Panel (C): Regression results

	i	ii	iii	iv
MATCH	-2.316***	-2.231***	-1.748***	-1.755***
	(0.240)	(0.285)	(0.258)	(0.261)
NUMCOM		0.257***	0.267***	0.265***
		(0.023)	(0.020)	(0.021)
lnNFORE_T		0.251**	0.125	0.133
		(0.123)	(0.106)	(0.109)
lnPACY		-0.071	0.050	0.043
		(0.099)	(0.103)	(0.102)
lnGEXP		-0.013	0.106	0.100
		(0.083)	(0.072)	(0.073)
lnBRO		-0.426***		
		(0.070)		
Constant	6.167***	3.336***	2.088**	2.113**
	(0.233)	(0.516)	(0.945)	(0.999)
No. of Observations	8,943	6,596	6,596	6,596
Adjusted R-Squared	0.081	0.380	0.512	0.511
Broker FE	No	No	Yes	Yes
Year FE	No	No	No	Yes

Table 3.3: Firms' analysts following

This table reports statistics and results for Hypothesis 2 – firms' analyst following by matching (non-matching) analysts is positively (negatively) associated with the R&D intensity. Panel (A) presents descriptive statistics for variables used in the regression. The dependent variable in general is the number of analysts following each firm. Precisely, they are total analyst following, regardless of their educational degrees (*AF_TOT*), the number of analysts having a matching educational degree (*AF_MA*), and the number of analysts not having a matching educational degree (*AF_nonMA*). *RD* denotes the R&D expense calculated by annual R&D expense scaled by total annual operating expense. *INTA* indicates the percentage of intangible assets in the balance sheet scaled by total assets. *lnMCAP* represents the market value of equity in the logarithm form. *RETVOL* is the stock return volatility. *RSQ* is the R-squared from the market model of the individual stock return. *INST* denotes the percentage of institutional ownership for a firm within a year. *BM* is the book-to-market ratio and measured by dividing the book value of equity by the market value of equity. *EFF* is analyst effort, calculated as the sum of the number of firms followed by all analysts for a firm divided by the number of analysts following the firm within a year, and then multiply by -1. Panel (B) reports Pearson (below diagonal) and Spearman (above diagonal) correlations. The correlations significant at the five percent level are shown in bold. Panel (C) outlines the results. Standard error is clustered at the firm and the year levels. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
AF_TOT	5,911	6.41	7.80	0	0	4	9	42
AF_MA	5,911	2.86	4.36	0	0	1	4	32
AF_nonMA	5,911	1.90	3.00	0	0	1	3	20
RD	5,911	0.36	0.31	0	0.04	0.30	0.67	1
INTA	5,911	0.13	0.18	0	0	0.04	0.20	0.74
lnMCAP	5,911	12.93	2.15	6.82	11.43	12.63	14.12	18.63
RETVOL	5,911	0.10	0.19	0	0.03	0.04	0.06	0.98
RSQ	5,911	0.13	0.15	0	0.01	0.07	0.20	0.62
INST	5,911	0.36	0.34	0	0	0.29	0.66	1
BM	5,911	0.36	0.41	-0.91	0.14	0.27	0.48	2.47
EFF	5,911	-10.54	8.70	-31.67	-17.39	-13	0	0

Panel (B): Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	*AF_TOT*		**0.85**	**0.82**	-0.02	**0.15**	**0.65**	**-0.48**	**0.51**	**0.78**	**-0.14**	**-0.67**
(2)	*AF_MA*	**0.79**		**0.53**	**0.26**	**-0.04**	**0.47**	**-0.28**	**0.34**	**0.64**	**-0.18**	**-0.64**
(3)	*AF_nonMA*	**0.77**	**0.31**		**-0.24**	**0.28**	**0.59**	**-0.50**	**0.51**	**0.69**	**-0.05**	**-0.54**
(4)	*RD*	**-0.07**	**0.22**	**-0.30**		**-0.42**	**-0.19**	**0.26**	**-0.18**	**-0.13**	**-0.25**	**-0.04**
(5)	*INTA*	**0.21**	**0.03**	**0.33**	**-0.32**		**0.35**	**-0.35**	**0.29**	**0.14**	**0.13**	-0.01
(6)	*lnMCAP*	**0.69**	**0.45**	**0.61**	**-0.22**	**0.35**		**-0.73**	**0.69**	**0.51**	**-0.19**	**-0.37**
(7)	*RETVOL*	**-0.27**	**-0.20**	**-0.22**	**-0.06**	**-0.07**	**-0.42**		**-0.68**	**-0.42**	**0.03**	**0.28**
(8)	*RSQ*	**0.45**	**0.24**	**0.48**	**-0.26**	**0.25**	**0.61**	**-0.33**		**0.47**	**-0.02**	**-0.33**
(9)	*INST*	**0.66**	**0.54**	**0.54**	**-0.12**	**0.10**	**0.47**	**-0.29**	**0.45**		**-0.03**	**-0.66**
(10)	*BM*	**-0.17**	**-0.18**	**-0.09**	**-0.19**	**0.03**	**-0.24**	**0.19**	**-0.03**	**-0.09**		**0.06**
(11)	*EFF*	**-0.50**	**-0.44**	**-0.38**	-0.02	-0.02	**-0.34**	**0.27**	**-0.29**	**-0.63**	**0.12**	

Panel (C): Regression results

	i	ii	iii
Dependent variable	AF_TOT	AF_MA	AF_nonMA
RD	1.781***	2.821***	-0.822***
	(0.482)	(0.360)	(0.213)
INTA	0.851	-0.975	1.671***
	(0.887)	(0.612)	(0.411)
lnMCAP	2.081***	0.935***	0.524***
	(0.181)	(0.127)	(0.076)
RETVOL	4.106***	2.842***	0.620**
	(0.540)	(0.428)	(0.221)
RSQ	-2.819	-2.691**	0.365
	(2.105)	(1.177)	(0.726)
INST	9.391***	5.415***	2.486***
	(1.151)	(0.689)	(0.389)
BM	0.459*	0.300*	0.007
	(0.247)	(0.162)	(0.128)
EFF	-0.085***	-0.045***	-0.025***
	(0.018)	(0.011)	(0.008)
No. of Observations	5,908	5,908	5,908
Adj. R-Squared	0.663	0.516	0.545
Industry × Year Fixed Effect	Yes	Yes	Yes

Table 3.4: Forecast accuracy

This table reports the test results for analysts' forecast accuracy. Panel (A) presents descriptive statistics. *FORERR* is the dependent variable, which is the analyst forecast error, calculated by taking the absolute value of the difference between the one-year-ahead EPS forecast and the actual EPS, scaled by the stock price two days before the forecast is provided, then multiplied by 100. *MATCH* is an indicator variable, equals to one if the analyst has a matching technological degree, and zero otherwise. *RD* denotes the R&D expense scaled by total annual operating expense. *INTA* indicates the percentage of intangible assets scaled by total assets. *LOSS* is a dummy variable, equals to one when the actual EPS in previous year is negative, and zero otherwise. *lnMCAP* represents the market value of equity in the logarithm form. *INST* denotes the percentage of institutional investor ownership. *BM* is the book-to-market ratio and measured by dividing the book value of equity by the market value of equity. *RETVOL* is the stock return volatility. *lnAF* is total analyst following in the logarithm form. *lnHOR* denotes the forecast horizon in the logarithm form. Forecast horizon is the number of days between the date when the forecast is provided and the date when the actual EPS is announced. *lnBRO* is the size of the employing brokerage house in the logarithm form, calculated as the number of analysts in each brokerage house within each year. *lnNUMCOM* denotes the number of firms followed by each analyst in the logarithm form. *lnNUMIND* is the number of industries (four-digit SIC) covered by an analyst in the logarithm form. *lnNFORE_T* is defined the number of forecasts provided by an analyst within a year in the logarithm form. *lnNFORE_F* is the number of forecasts provided by each analyst for each firm within a year in the logarithm form. *lnPACY* denotes the relative accuracy score of an analyst in the previous year in the logarithm form, which is calculated in line with Hong and Kubik (2003). *lnFEXP* is analysts' coverage history for a specific firm in the logarithm form. Coverage history is measured as the number of years since the analyst provided her first forecast for the specific firm to present. *lnGEXP* is analysts' general experience of being an analyst in the logarithm form. Analysts' general experience is measured as the number of years from when the analyst issued her first forecast for any firms to present. Panel (B) reports Pearson (below diagonal) and Spearman (above diagonal) correlations. The correlations significant at the five percent level are shown in bold. Panel (C) outlines the results. Models (i) and (ii) use the full sample. Models (iii) and (iv) use the last forecast provided by each analyst for each firm with each year. Models (v) and (vi) use forecasts made in the week following earnings announcement. All the regressions are clustered at the analyst level and the year levels. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

MATCH=1								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
FORERROR	58,656	1.90	3.49	0	0.17	0.6	1.94	21.43
RD	58,656	0.42	0.28	0	0.19	0.39	0.69	1.02
INTA	58,656	0.16	0.20	0	0	0.07	0.29	0.76
LOSS	58,656	0.51	0.50	0	0	1	1	1
lnMCAP	58,656	14.81	2.13	8.18	13.21	14.54	16.55	19.1
INST	58,656	0.63	0.31	0	0.47	0.72	0.87	1
BM	58,656	0.26	0.23	-0.38	0.11	0.22	0.36	1.23
RETVOL	58,656	0.04	0.03	0.01	0.02	0.03	0.04	0.2
lnAF	58,656	2.63	0.68	0	2.2	2.71	3.18	3.74
lnHOR	58,656	5.28	0.50	2.83	4.82	5.34	5.69	5.9
lnBRO	58,656	3.78	1.10	0	3	3.93	4.68	5.63
lnNUMCOM	58,656	2.81	0.44	0	2.56	2.89	3.09	3.74
lnNUMIND	58,656	1.18	0.60	0	0.69	1.1	1.39	2.77
lnNFORE_T	58,656	4.25	0.55	0	3.99	4.33	4.62	5.67
lnNFORE_F	58,656	1.55	0.53	0	1.39	1.61	1.95	4.44
lnPACY	58,656	3.93	0.26	1.43	3.84	3.97	4.09	4.61
lnFEXP	58,656	6.09	1.99	0	5.53	6.54	7.35	9.21
lnGEXP	58,656	7.89	0.91	3.78	7.33	7.99	8.6	9.41

MATCH=0								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
FORERROR	39,176	1.32	2.84	0	0.09	0.34	1.21	21.43
RD	39,176	0.19	0.25	0	0.02	0.08	0.28	1.02
INTA	39,176	0.23	0.20	0	0.05	0.19	0.36	0.76
LOSS	39,176	0.27	0.44	0	0	0	1	1
lnMCAP	39,176	15.21	2.08	8.87	13.61	15.23	16.85	19.1
INST	39,176	0.61	0.30	0	0.51	0.68	0.83	1
BM	39,176	0.31	0.24	-0.38	0.16	0.26	0.42	1.23
RETVOL	39,176	0.03	0.02	0.01	0.02	0.02	0.03	0.2
lnAF	39,176	2.60	0.69	0	2.08	2.71	3.14	3.74
lnHOR	39,176	5.26	0.51	3	4.8	5.32	5.68	5.9
lnBRO	39,176	3.83	1.03	0	3.22	3.97	4.7	5.63
lnNUMCOM	39,176	2.77	0.46	0	2.56	2.83	3.04	3.74
lnNUMIND	39,176	1.62	0.73	0	1.1	1.79	2.2	2.77
lnNFORE_T	39,176	4.22	0.54	0	3.99	4.3	4.57	6.58
lnNFORE_F	39,176	1.54	0.51	0	1.39	1.61	1.79	4.53
lnPACY	39,176	3.93	0.24	0.01	3.82	3.96	4.08	4.61
lnFEXP	39,176	6.42	1.93	0	5.79	6.8	7.64	9.41
lnGEXP	39,176	8.14	0.94	3.64	7.55	8.34	8.92	9.44

Panel (B): Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1)	*FORERROR*		**0.28**	**-0.36**	**0.14**	**0.45**	**-0.56**	**-0.11**	**0.05**	**0.52**	**-0.41**	**0.28**	**-0.13**	**0.10**	**-0.14**	**0.01**	**-0.07**	**-0.01**	**-0.22**	**-0.11**
(2)	*RD*	**0.24**		**-0.42**	**0.42**	**0.60**	**-0.31**	**-0.03**	**-0.26**	**0.45**	**-0.09**	**0.05**	**-0.09**	**0.10**	**-0.57**	**-0.05**	**-0.19**	**0.04**	**-0.22**	**-0.16**
(3)	*INTA*	**-0.21**	**-0.37**		**-0.21**	**-0.52**	**0.56**	**0.04**	**0.23**	**-0.53**	**0.37**	**-0.04**	**0.12**	**-0.10**	**0.14**	**0.02**	**0.20**	0.00	**0.22**	**0.15**
(4)	*MATCH*	**0.09**	**0.39**	**-0.16**		**0.24**	**-0.10**	**0.05**	**-0.11**	**0.21**	**0.02**	**0.02**	**-0.01**	**0.05**	**-0.31**	**0.03**	**0.02**	**0.02**	**-0.10**	**-0.15**
(5)	*LOSS*	**0.31**	**0.64**	**-0.40**	**0.24**		**-0.60**	**-0.13**	**-0.20**	**0.61**	**-0.38**	**0.06**	**-0.13**	**0.12**	**-0.29**	**-0.02**	**-0.22**	**0.02**	**-0.28**	**-0.16**
(6)	*lnMCAP*	**-0.43**	**-0.35**	**0.49**	**-0.09**	**-0.59**		**0.11**	**-0.07**	**-0.70**	**0.77**	**-0.07**	**0.26**	**-0.11**	**0.03**	**0.05**	**0.29**	0.00	**0.35**	**0.21**
(7)	*INST*	**-0.17**	**-0.08**	**-0.01**	**0.03**	**-0.16**	**0.14**		**-0.07**	**-0.11**	**0.28**	**-0.01**	**0.04**	**-0.09**	**0.01**	**-0.04**	**0.13**	0.00	**0.09**	**-0.08**
(8)	*BM*	**0.06**	**-0.21**	**0.17**	**-0.11**	**-0.13**	**-0.12**	**-0.07**		**-0.09**	**-0.10**	**-0.01**	0.00	**-0.04**	**0.15**	**0.03**	**0.07**	0.00	**0.03**	**0.03**
(9)	*RETVOL*	**0.33**	**0.33**	**-0.29**	**0.13**	**0.40**	**-0.48**	**-0.15**	0.00		**-0.47**	**0.06**	**-0.17**	**0.14**	**-0.21**	0.00	**-0.17**	**0.01**	**-0.32**	**-0.17**
(10)	*lnAF*	**-0.34**	**-0.14**	**0.32**	**0.02**	**-0.35**	**0.74**	**0.33**	**-0.14**	**-0.35**		**-0.05**	**0.21**	**-0.08**	**-0.11**	**0.03**	**0.26**	0.00	**0.29**	**0.09**
(11)	*lnHOR*	**0.15**	**0.05**	**-0.03**	**0.02**	**0.06**	**-0.06**	**-0.01**	0.00	**0.03**	**-0.04**		**-0.03**	**0.02**	**-0.03**	**-0.02**	0.00	**0.01**	**-0.04**	**-0.04**
(12)	*lnBRO*	**-0.09**	**-0.05**	**0.10**	**-0.02**	**-0.10**	**0.24**	**0.04**	**-0.03**	**-0.12**	**0.21**	**-0.02**		**0.01**	**-0.02**	**0.20**	**0.20**	**0.04**	**0.09**	**0.10**
(13)	*lnNUMCOM*	**0.07**	**0.10**	**-0.07**	**0.05**	**0.10**	**-0.10**	**-0.09**	**-0.02**	**0.08**	**-0.06**	**0.02**	**-0.01**		**0.28**	**0.76**	**-0.05**	0.00	**0.10**	**0.25**
(14)	*lnNUMIND*	**-0.10**	**-0.50**	**0.06**	**-0.31**	**-0.29**	**0.02**	**0.04**	**0.13**	**-0.13**	**-0.10**	**-0.03**	**-0.08**	**0.33**		**0.26**	**0.01**	**-0.07**	**0.17**	**0.14**
(15)	*lnNFORE_T*	0.00	**-0.04**	**0.02**	**0.03**	**-0.04**	**0.05**	**-0.03**	**0.03**	**-0.01**	**0.04**	**-0.02**	**0.15**	**0.79**	**0.30**		**0.33**	**0.03**	**0.20**	**0.26**
(16)	*lnNFORE_F*	**-0.10**	**-0.19**	**0.16**	**0.01**	**-0.20**	**0.25**	**0.11**	**0.06**	**-0.14**	**0.22**	**0.02**	**0.17**	**-0.02**	**0.02**	**0.38**		**0.04**	**0.24**	**0.02**
(17)	*lnPACY*	**-0.01**	**0.01**	**0.02**	0.00	0.00	**0.01**	0.00	0.00	**-0.01**	0.00	**0.02**	**0.05**	**0.08**	**-0.01**	**0.14**	**0.08**		**0.02**	**-0.04**
(18)	*lnFEXP*	**-0.15**	**-0.20**	**0.13**	**-0.08**	**-0.23**	**0.29**	**0.10**	**0.01**	**-0.21**	**0.25**	**-0.02**	**0.07**	**0.09**	**0.13**	**0.20**	**0.35**	**0.07**		**0.38**
(19)	*lnGEXP*	**-0.07**	**-0.15**	**0.11**	**-0.13**	**-0.15**	**0.19**	**-0.06**	**0.01**	**-0.11**	**0.09**	**-0.05**	**0.09**	**0.28**	**0.14**	**0.27**	**0.02**	0.01	**0.29**	

Panel (C): Regression results

	All forecasts		Last forecasts		Forecasts after EA	
	i	ii	iii	iv	v	vi
RD	0.527*	0.847**	0.186	0.524**	0.625**	0.933***
	(0.249)	(0.286)	(0.222)	(0.202)	(0.267)	(0.303)
INTA	0.195	-0.044	0.346**	0.028	0.398**	0.179
	(0.170)	(0.169)	(0.151)	(0.115)	(0.179)	(0.156)
MATCH	0.060	0.102	0.112*	0.145	0.082*	0.138
	(0.043)	(0.083)	(0.058)	(0.094)	(0.046)	(0.093)
MATCH × *RD*		-0.430**		-0.453***		-0.416**
		(0.152)		(0.148)		(0.172)
MATCH × *INTA*		0.410		0.562**		0.380
		(0.234)		(0.229)		(0.239)
LOSS	0.080	0.083	0.073	0.076	-0.107	-0.106
	(0.174)	(0.175)	(0.188)	(0.186)	(0.198)	(0.200)
lnMCAP	-0.492***	-0.493***	-0.456***	-0.458***	-0.557***	-0.558***
	(0.048)	(0.048)	(0.059)	(0.059)	(0.057)	(0.057)
INST	-0.872***	-0.865***	-1.125***	-1.119***	-0.898***	-0.894***
	(0.257)	(0.257)	(0.320)	(0.318)	(0.276)	(0.276)
BM	0.442**	0.433**	0.320	0.307	0.328*	0.321*
	(0.177)	(0.177)	(0.212)	(0.216)	(0.175)	(0.177)
RETVOL	14.370***	14.378***	12.634***	12.609***	12.674***	12.683***
	(2.928)	(2.917)	(2.559)	(2.549)	(2.929)	(2.927)
lnAF	-0.205**	-0.208**	-0.068	-0.072	-0.093	-0.096
	(0.088)	(0.087)	(0.084)	(0.083)	(0.091)	(0.090)
lnHOR	0.788***	0.788***	0.568***	0.566***	1.007***	1.005***
	(0.095)	(0.095)	(0.105)	(0.105)	(0.115)	(0.115)
lnBRO	0.052**	0.058**	0.081***	0.087***	0.058**	0.065***
	(0.019)	(0.020)	(0.022)	(0.022)	(0.019)	(0.020)
lnNUMCOM	0.378***	0.385***	0.126	0.135	0.327***	0.339***
	(0.115)	(0.115)	(0.119)	(0.116)	(0.106)	(0.103)
lnNUMIND	-0.275***	-0.266***	-0.239***	-0.230***	-0.252***	-0.242***
	(0.058)	(0.059)	(0.069)	(0.069)	(0.061)	(0.060)
lnNFORE_T	-0.149	-0.166	0.084	0.070	-0.130	-0.152*
	(0.098)	(0.099)	(0.096)	(0.095)	(0.081)	(0.077)
lnNFORE_F	0.128	0.125	-0.278***	-0.282***	0.125	0.122
	(0.082)	(0.082)	(0.083)	(0.083)	(0.078)	(0.078)
lnPACY	-0.122*	-0.118*	-0.051	-0.048	-0.093	-0.092
	(0.062)	(0.062)	(0.079)	(0.078)	(0.077)	(0.077)
lnFEXP	-0.018	-0.018	-0.018	-0.018	0.025	0.025
	(0.013)	(0.014)	(0.018)	(0.017)	(0.017)	(0.017)
lnGEXP	0.046	0.041	0.056*	0.050	0.032	0.026
	(0.028)	(0.028)	(0.031)	(0.031)	(0.030)	(0.029)
Observations	97,831	97,831	26,342	26,342	60,808	60,808
Adjusted R2	0.257	0.258	0.232	0.233	0.250	0.251
Industry × Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.5: Market reaction to recommendation revisions

This table reports the results for the test of the market reaction to recommendation revisions. Panel (A) presents descriptive statistics. The dependent variable (*CAR*) in general is 5-day [-1, 3] cumulative abnormal CRSP value-weighted adjusted return to recommendation revisions in the percentage form. *CAR_nonD* is *CAR* to all recommendation revisions with an adjustment of multiplying market reactions to downward revisions by -1. *CAR_UP* is *CAR* to upward recommendation revisions only. *CAR_DOWN* is *CAR* to downward recommendation revisions only. *MATCH* is an indicator variable, equals to one if the analyst has a matching technological degree, and zero otherwise. *RD* denotes the R&D expense scaled by total annual operating expense. *lnPACY* denotes the relative accuracy score of an analyst in the previous year in the natural logarithm form, which is calculated in line with Hong and Kubik (2003). *lnFEXP* is analysts' coverage history for a specific firm in the logarithm form. Coverage history is measured as the number of years since the analyst provided her first forecast for the specific firm to present. *lnGEXP* is analysts' general experience of being an analyst in the logarithm form. Analysts' general experience is measured as the number of years from when the analyst issued her first forecast for any firms to present. *lnNUMCOM* denotes the number of firms followed by each analyst in the logarithm form. *lnNUMIND* is the number of industries (four-digit SIC) covered by an analyst in the logarithm form. *INTA* indicates the percentage of intangible assets scaled by total assets. *lnAF* is total analyst following in the logarithm form. *lnMCAP* represents the market value of equity in the logarithm form. *BM* is the book-to-market ratio and measured by dividing the book value of equity by the market value of equity. *RETVOL_PC* is the stock return volatility in percentage. *INST* denotes the percentage of institutional investor ownership. *EARNANN* is the dummy variable with the value of one on the earnings announcement day, and zero otherwise. Panel (B) reports Pearson (below diagonal) and Spearman (above diagonal) correlations for the sample with the non-directional dependent variable only. The correlations significant at the five percent level are shown in bold. Panel (C) outlines the results. All the regressions are clustered at the firm and the year levels. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
CAR_nonD	8,986	5.75	14.68	-26.45	-0.86	2.52	7.92	74.83
CAR_UP	4,214	4.05	11.31	-64.45	-0.84	2.44	6.95	51.69
CAR_DOWN	4,772	-6.61	16.42	-64.45	-9.08	-2.64	0.89	51.69
MATCH	8,986	0.66	0.47	0	0	1	1	1
RD	8,986	0.26	0.28	0	0.02	0.14	0.44	0.97
lnPACY	8,986	3.95	0.31	0	3.87	4	4.1	4.62
lnFEXP	8,986	6.58	1.16	0	5.9	6.67	7.38	9.36
lnGEXP	8,986	7.89	0.88	3.76	7.45	7.94	8.56	9.4
lnNUMCOM	8,986	2.90	0.58	0	2.56	2.83	3.26	4.08
lnNUMIND	8,986	0.91	0.82	0	0	0.69	1.79	3.09
INTA	8,986	0.17	0.18	0	0	0.1	0.28	0.72
lnAF	8,986	2.56	0.69	0	2.2	2.64	3.09	3.74
lnMCAP	8,986	14.86	1.95	8.08	13.51	14.71	16.36	19.03
BM	8,986	0.33	0.28	-0.39	0.16	0.27	0.45	1.48
RETVOL_PC	8,986	3.43	2.68	0.61	1.88	2.86	4.12	19.58
INST	8,986	0.69	0.25	0	0.58	0.74	0.87	1
EARNANN	8,986	0.05	0.22	0	0	0	0	1

Panel (B): Correlation Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	*CAR_nonD*		**0.04**	**0.16**	**0.02**	**-0.05**	-0.01	**-0.03**	**-0.14**	**-0.18**	**-0.08**	**-0.22**	**-0.03**	**0.21**	-0.02	**0.02**
(2)	*MATCH*	**0.07**		**0.16**	**0.09**	**-0.08**	**-0.15**	**0.23**	**0.02**	**-0.21**	0.00	**-0.04**	-0.01	**0.18**	**0.03**	-0.01
(3)	*RD*	**0.27**	**0.19**		**-0.07**	**-0.07**	**-0.15**	**-0.28**	**-0.68**	**-0.25**	**0.08**	**-0.23**	**-0.33**	**0.21**	**0.05**	0.01
(4)	*lnPACY*	**0.02**	**0.05**	**-0.08**		0.02	0.01	**0.13**	**0.08**	-0.02	**-0.04**	-0.01	**0.07**	**0.09**	-0.01	-0.01
(5)	*lnFEXP*	**-0.07**	**-0.09**	**-0.12**	**0.07**		**0.42**	**0.06**	**0.06**	**0.20**	**0.23**	**0.29**	**0.03**	**-0.27**	**0.09**	0.00
(6)	*lnGEXP*	**-0.03**	**-0.11**	**-0.17**	**0.08**	**0.41**		**0.12**	**0.09**	**0.15**	**0.13**	**0.20**	**0.03**	**-0.15**	**-0.05**	**-0.04**
(7)	*lnNUMCOM*	**-0.04**	**0.25**	**-0.22**	**0.21**	**0.03**	**0.17**		**0.62**	**-0.05**	**-0.13**	0.01	**0.17**	**0.13**	**-0.03**	-0.01
(8)	*lnNUMIND*	**-0.17**	**0.02**	**-0.58**	**0.13**	**0.05**	**0.13**	**0.65**		**0.10**	**-0.23**	**0.07**	**0.30**	**-0.06**	**-0.05**	-0.01
(9)	*INTA*	**-0.17**	**-0.19**	**-0.25**	0.00	**0.14**	**0.11**	**-0.08**	**0.00**		**0.30**	**0.47**	**0.19**	**-0.51**	**0.10**	**0.03**
(10)	*lnAF*	**-0.09**	0.01	0.02	0.00	**0.23**	**0.11**	**-0.12**	**-0.21**	**0.27**		**0.71**	**-0.17**	**-0.39**	**0.27**	**0.03**
(11)	*lnMCAP*	**-0.27**	**-0.05**	**-0.31**	0.02	**0.27**	**0.20**	0.00	**0.04**	**0.40**	**0.65**		**-0.11**	**-0.63**	**0.11**	**0.05**
(12)	*BM*	0.01	0.01	**-0.25**	**0.07**	**0.03**	**0.02**	**0.19**	**0.26**	**0.08**	**-0.18**	**-0.17**		-0.02	**-0.09**	-0.01
(13)	*RETVOL_PC*	**0.29**	**0.10**	**0.29**	0.01	**-0.17**	**-0.12**	**0.05**	**-0.08**	**-0.30**	**-0.28**	**-0.47**	**0.03**		**-0.11**	**-0.06**
(14)	*INST*	**-0.08**	**0.02**	**-0.03**	**0.03**	**0.10**	**-0.02**	**-0.02**	-0.03	**0.08**	**0.39**	**0.15**	**-0.09**	**-0.14**		0.01
(15)	*EARNANN*	0.01	**-0.01**	0.00	-0.01	0.00	**-0.04**	-0.01	-0.01	**0.02**	**0.03**	**0.05**	-0.02	-0.05	0.01	

Panel (C): Regression results

	Non-directional		Upward revisions		Downward revisions	
	i	ii	iii	iv	v	vi
RD	3.145	1.598	3.492*	0.404	-0.938	-0.712
	(1.882)	(2.090)	(1.821)	(2.407)	(2.547)	(2.769)
MATCH	1.015**	0.487	1.052***	0.024	-0.958	-0.878
	(0.378)	(0.427)	(0.330)	(0.448)	(0.717)	(0.636)
MATCH_RD		2.112*		4.184**		-0.310
		(1.118)		(1.838)		(2.395)
lnPACY	2.084**	2.092**	2.122*	2.152*	-1.482	-1.482
	(0.833)	(0.830)	(1.007)	(1.010)	(1.079)	(1.078)
lnFEXP	0.008	0.011	0.133	0.133	0.118	0.117
	(0.129)	(0.137)	(0.168)	(0.158)	(0.181)	(0.182)
lnGEXP	0.657***	0.666***	0.426	0.438	-0.773***	-0.775**
	(0.212)	(0.207)	(0.290)	(0.290)	(0.253)	(0.256)
lnNUMCOM	0.656	0.745	-0.028	0.166	-1.710**	-1.723**
	(0.647)	(0.646)	(0.831)	(0.769)	(0.629)	(0.613)
lnNUMIND	-0.971*	-0.977*	-0.340	-0.360	1.976**	1.977**
	(0.543)	(0.542)	(0.276)	(0.284)	(0.903)	(0.902)
INTA	-4.444***	-4.461***	-1.546	-1.544	5.607***	5.612***
	(1.324)	(1.313)	(1.090)	(1.066)	(1.455)	(1.461)
lnAF	2.248**	2.248**	-1.636**	-1.636**	-4.803***	-4.803***
	(0.884)	(0.887)	(0.671)	(0.665)	(1.179)	(1.179)
lnMCAP	-1.573***	-1.564***	0.138	0.158	2.865***	2.864***
	(0.385)	(0.386)	(0.303)	(0.310)	(0.435)	(0.435)
BM	4.880	4.923	-2.486***	-2.432***	-7.739	-7.745
	(3.122)	(3.108)	(0.733)	(0.770)	(4.409)	(4.405)
RETVOL_PC	1.113***	1.111***	0.830***	0.827***	-0.870***	-0.870***
	(0.215)	(0.211)	(0.172)	(0.177)	(0.239)	(0.239)
INST	-2.217	-2.218	3.208**	3.172**	5.144*	5.142*
	(1.823)	(1.821)	(1.164)	(1.159)	(2.694)	(2.693)
EARNANN	1.303*	1.299*	-0.048	-0.019	-2.326**	-2.324**
	(0.695)	(0.704)	(0.697)	(0.712)	(0.997)	(0.997)
Observations	8,981	8,981	4,197	4,197	4,757	4,757
Adjusted R2	0.172	0.173	0.077	0.079	0.230	0.230
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.6: Boldness

This table presents the results for the test of analysts' boldness, both in the full sample and in the sample with pharmaceutical firms only (SIC 2833-2836). Panel (A) presents descriptive statistics for the full sample and the pharma sample. The dependent variable is analysts' boldness (*BOLD*). *BOLD* is an indicator variable, equal to one if an analyst's forecast is above both her prior forecast and the consensus forecast immediately before her forecast revision, or else below both, otherwise zero. The consensus forecast is the mean of forecasts provided by all analysts within 90 days prior to the analyst's forecast. *MATCH* is an indicator variable, equals to one if the analyst has a matching technological degree, and zero otherwise. *RD* denotes the R&D expense scaled by total annual operating expense. *lnPACY* denotes the relative accuracy score of an analyst in the previous year in the natural logarithm form, which is calculated in line with Hong and Kubik (2003). *lnNUMCOM* denotes the number of firms followed by each analyst in the logarithm form. *lnNUMIND* is the number of industries (four-digit SIC) covered by an analyst in the logarithm form. *lnNFORE_T* is defined the number of forecasts provided by an analyst within a year in the logarithm form. *lnNFORE_F* is the number of forecasts provided by each analyst for each firm within a year in the logarithm form. *INTA* indicates the percentage of intangible assets scaled by total assets. *lnAF* is total analyst following in the logarithm form. *lnMCAP* represents the market value of equity in the logarithm form. *INST* denotes the percentage of institutional investor ownership. *BM* is the book-to-market ratio and measured by dividing the book value of equity by the market value of equity. *lnBRO* is the size of the employing brokerage house in the logarithm form, calculated as the number of analysts in each brokerage house within each year. *lnHOR* denotes the forecast horizon in the logarithm form. Forecast horizon is the number of days between the date when the forecast is provided and the date when the actual EPS is announced. *lnFEXP* is analysts' coverage history for a specific firm in the logarithm form. Coverage history is measured as the number of years since the analyst provided her first forecast for the specific firm to present. *lnGEXP* is analysts' general experience of being an analyst in the logarithm form. Analysts' general experience is measured as the number of years from when the analyst issued her first forecast for any firms to present. *lnELAPSE* is the number of days since last forecast made by any analyst in the logarithm form. Panel (B) reports Pearson (below diagonal) and Spearman (above diagonal) correlations. The correlations significant at the five percent level are shown in bold. Panels (C) and (D) outlines the results for the full sample and pharma only sample respectively. The tests are conducted by logistic regressions. All the regressions are clustered at the analyst levels. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics

Full sample: MATCH=1								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
BOLD	44,622	0.71	0.45	0	0	1	1	1
RD	44,622	0.41	0.28	0	0.18	0.37	0.67	0.99
lnPACY	44,622	3.95	0.29	0	3.86	3.99	4.10	4.62
lnNUMCOM	44,622	2.82	0.43	0	2.56	2.89	3.09	4.03
lnNFORE_T	44,622	4.30	0.51	0	4.04	4.36	4.62	5.67
lnNFORE_F	44,622	1.65	0.45	0	1.39	1.61	1.95	4.44
lnNUMIND	44,622	1.18	0.61	0	0.69	1.10	1.39	3
INTA	44,622	0.17	0.20	0	0	0.08	0.31	0.78
lnAF	44,622	2.68	0.65	0	2.20	2.77	3.18	3.74
RETVOL	44,622	0.03	0.03	0.01	0.02	0.03	0.04	0.19
lnMCAP	44,622	14.92	2.11	8.08	13.34	14.68	16.65	19.11
INST	44,622	0.64	0.31	0	0.50	0.72	0.87	1
BM	44,622	0.25	0.35	-13.03	0.11	0.22	0.36	1.15
lnHOR	44,622	5.18	0.47	2.89	4.77	5.28	5.63	5.86
lnBRO	44,622	3.81	1.10	0	3.09	3.97	4.71	5.63
lnFEXP	44,622	6.50	1.26	0.69	5.77	6.64	7.41	8.97
lnGEXP	44,622	7.91	0.89	3.78	7.36	8	8.61	9.31
lnELAPSE	44,622	1.48	1.44	0	0	1.10	2.64	4.47

Full sample: MATCH=0								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
BOLD	29,677	0.75	0.43	0	0	1	1	1
RD	29,677	0.19	0.24	0	0.02	0.08	0.27	0.99
lnPACY	29,677	3.95	0.25	0	3.85	3.99	4.09	4.62
lnNUMCOM	29,677	2.77	0.45	0	2.56	2.83	3.04	4.32
lnNFORE_T	29,677	4.25	0.50	0	4.03	4.33	4.58	6.58
lnNFORE_F	29,677	1.63	0.44	0	1.39	1.61	1.95	4.53
lnNUMIND	29,677	1.63	0.74	0	1.10	1.79	2.20	3.47
INTA	29,677	0.23	0.20	0	0.05	0.19	0.36	0.78
lnAF	29,677	2.62	0.67	0	2.20	2.77	3.18	3.74
RETVOL	29,677	0.03	0.02	0.01	0.02	0.02	0.03	0.19
lnMCAP	29,677	15.27	2.05	8.87	13.71	15.3	16.87	19.11
INST	29,677	0.61	0.30	0	0.52	0.69	0.83	1
BM	29,677	0.31	0.26	-11.44	0.16	0.27	0.42	1.15
lnHOR	29,677	5.15	0.47	3.04	4.73	5.25	5.61	5.86
lnBRO	29,677	3.87	1.01	0	3.30	4.01	4.72	5.63
lnFEXP	29,677	6.74	1.29	0.69	5.96	6.88	7.68	8.97
lnGEXP	29,677	8.15	0.92	3.87	7.56	8.34	8.92	9.31
lnELAPSE	29,677	1.50	1.41	0	0	1.39	2.64	4.47

(*continued on next page*)

Table 3.6 Panel (A) (continued)

Pharma only: MATCH=1								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
BOLD	38,225	0.70	0.46	0	0	1	1	1
RD	38,225	0.47	0.25	0	0.27	0.44	0.71	0.99
lnPACY	38,225	3.95	0.30	0	3.86	3.99	4.11	4.62
lnNUMCOM	38,225	2.80	0.44	0	2.56	2.83	3.09	4.03
lnNFORE_T	38,225	4.25	0.49	0	4.03	4.32	4.60	5.35
lnNFORE_F	38,225	1.63	0.45	0	1.39	1.61	1.95	4.44
lnNUMIND	38,225	1.01	0.46	0	0.69	1.10	1.10	2.89
INTA	38,225	0.17	0.21	0	0	0.05	0.32	0.78
lnAF	38,225	2.68	0.67	0	2.20	2.77	3.22	3.74
RETVOL	38,225	0.04	0.03	0.01	0.02	0.03	0.04	0.19
lnMCAP	38,225	14.80	2.18	8.08	13.18	14.46	16.65	19.11
INST	38,225	0.63	0.32	0	0.46	0.73	0.89	1
BM	38,225	0.22	0.37	-13.03	0.10	0.20	0.34	1.15
lnHOR	38,225	5.19	0.46	3.18	4.78	5.29	5.63	5.86
lnBRO	38,225	3.84	0.98	0	3.09	3.93	4.67	5.63
lnFEXP	38,225	6.40	1.24	0.69	5.68	6.55	7.29	8.97
lnGEXP	38,225	7.82	0.88	3.78	7.28	7.91	8.48	9.31
lnELAPSE	38,225	1.50	1.47	0	0	1.1	2.71	4.47

Pharma only: MATCH=0								
Variable	N	Mean	S.D.	Min	0.25	Median	0.75	Max
BOLD	16,317	0.73	0.44	0	0	1	1	1
RD	16,317	0.33	0.25	0	0.12	0.25	0.48	0.99
lnPACY	16,317	3.96	0.24	0	3.87	4	4.11	4.62
lnNUMCOM	16,317	2.77	0.47	0	2.56	2.83	3.04	4.08
lnNFORE_T	16,317	4.21	0.50	0.69	3.97	4.26	4.53	5.47
lnNFORE_F	16,317	1.60	0.46	0	1.39	1.61	1.79	4.53
lnNUMIND	16,317	1.19	0.63	0	0.69	1.10	1.61	3.47
INTA	16,317	0.23	0.23	0	0.01	0.18	0.38	0.78
lnAF	16,317	2.63	0.69	0	2.20	2.77	3.18	3.74
RETVOL	16,317	0.03	0.02	0.01	0.02	0.03	0.04	0.19
lnMCAP	16,317	15.08	2.26	8.87	13.33	14.86	17.09	19.11
INST	16,317	0.60	0.32	0	0.42	0.68	0.85	1
BM	16,317	0.27	0.25	-11.44	0.15	0.24	0.37	1.15
lnHOR	16,317	5.18	0.46	3.04	4.75	5.28	5.62	5.86
lnBRO	16317	3.79	0.95	0	3.04	3.83	4.62	5.63
lnFEXP	16,317	6.62	1.32	0.69	5.83	6.72	7.55	8.97
lnGEXP	16,317	8.18	0.91	3.87	7.62	8.36	8.92	9.31
lnELAPSE	16,317	1.52	1.48	0	0	1.39	2.71	4.47

Panel (B): Correlation Matrix

Full Sample																				
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1)	*BOLD*		**-0.04**	**-0.08**	**0.01**	**-0.01**	-0.01	0.00	**0.05**	**0.04**	**0.01**	**-0.04**	**0.03**	**0.01**	**0.02**	**-0.02**	**0.01**	**0.02**	**0.02**	**-0.01**
(2)	*MATCH*	**-0.04**		**0.41**	**0.02**	**0.06**	**0.05**	**0.02**	**-0.30**	**-0.20**	**0.04**	**0.19**	**-0.08**	**0.06**	**-0.11**	**0.04**	**-0.01**	**-0.09**	**-0.14**	**-0.01**
(3)	*RD*	**-0.08**	**0.38**		**0.04**	**0.09**	**-0.06**	**-0.20**	**-0.58**	**-0.40**	**-0.06**	**0.43**	**-0.28**	**-0.01**	**-0.28**	**0.07**	**-0.09**	**-0.20**	**-0.16**	**0.06**
(4)	*lnPACY*	**0.01**	0.00	0.00		0.00	**0.02**	**0.04**	**-0.07**	0.00	0.00	**0.01**	0.00	0.00	0.00	**0.02**	**0.04**	**0.02**	**-0.04**	0.00
(5)	*lnNUMCOM*	**-0.01**	**0.05**	**0.10**	**0.09**		**0.75**	**-0.08**	**0.28**	**-0.10**	**-0.08**	**0.14**	**-0.11**	**-0.09**	**-0.05**	**0.02**	0.00	**0.11**	**0.25**	**0.05**
(6)	*lnNFORE_T*	0.00	**0.04**	**-0.05**	**0.15**	**0.79**		**0.30**	**0.27**	**0.02**	**0.03**	0.00	**0.05**	**-0.05**	**0.03**	**0.01**	**0.19**	**0.20**	**0.27**	**0.03**
(7)	*lnNFORE_F*	-0.01	**0.02**	**-0.20**	**0.07**	**-0.07**	**0.33**		0.00	**0.21**	**0.25**	**-0.17**	**0.29**	**0.11**	**0.08**	**0.06**	**0.20**	**0.17**	**0.01**	**-0.07**
(8)	*lnNUMIND*	**0.05**	**-0.31**	**-0.50**	**-0.01**	**0.34**	**0.31**	0.00		**0.12**	**-0.13**	**-0.20**	**0.01**	0.00	**0.15**	**-0.06**	**-0.02**	**0.16**	**0.14**	**0.03**
(9)	*INTA*	**0.03**	**-0.15**	**-0.35**	**0.02**	**-0.08**	**0.03**	**0.18**	**0.04**		**0.36**	**-0.52**	**0.55**	**0.02**	**0.24**	**-0.05**	**0.12**	**0.20**	**0.14**	**-0.14**
(10)	*lnAF*	0.00	**0.04**	**-0.12**	**0.01**	**-0.06**	**0.04**	**0.21**	**-0.11**	**0.31**		**-0.46**	**0.77**	**0.25**	**-0.10**	**-0.07**	**0.20**	**0.27**	**0.09**	**-0.32**
(11)	*RETVOL*	**-0.03**	**0.13**	**0.33**	**-0.01**	**0.09**	**-0.01**	**-0.14**	**-0.13**	**-0.30**	**-0.33**		**-0.69**	**-0.08**	**-0.09**	**0.10**	**-0.17**	**-0.31**	**-0.17**	**0.16**
(12)	*lnMCAP*	**0.03**	**-0.08**	**-0.34**	**0.02**	**-0.11**	**0.06**	**0.27**	0.01	**0.48**	**0.73**	**-0.49**		**0.07**	**-0.06**	**-0.10**	**0.26**	**0.34**	**0.21**	**-0.27**
(13)	*INST*	**0.02**	**0.04**	**-0.07**	0.01	**-0.09**	**-0.04**	**0.09**	**0.03**	**-0.03**	**0.30**	**-0.13**	**0.11**		**-0.07**	**-0.02**	**0.02**	**0.07**	**-0.09**	**-0.10**
(14)	*BM*	**0.01**	**-0.09**	**-0.18**	0.00	**-0.03**	**0.02**	**0.07**	**0.10**	**0.15**	**-0.09**	**-0.05**	**-0.03**	**-0.03**		**0.00**	0.00	**0.03**	**0.03**	0.01
(15)	*lnBRO*	**-0.02**	**0.03**	**0.06**	**0.02**	**0.01**	**0.01**	**0.06**	**-0.05**	**-0.03**	**-0.06**	**0.06**	**-0.09**	**-0.03**	**-0.01**		**-0.02**	**-0.08**	**-0.05**	**0.04**
(16)	*lnHOR*	**0.01**	**-0.03**	**-0.05**	**0.06**	**-0.04**	**0.13**	**0.17**	**-0.08**	**0.10**	**0.21**	**-0.12**	**0.24**	**0.03**	**-0.02**	**-0.01**		**0.09**	**0.10**	0.00
(17)	*lnFEXP*	**0.02**	**-0.09**	**-0.20**	**0.09**	**0.12**	**0.20**	**0.18**	**0.15**	**0.13**	**0.26**	**-0.22**	**0.32**	**0.08**	**0.01**	**-0.07**	**0.07**		**0.39**	**-0.09**
(18)	*lnGEXP*	**0.02**	**-0.13**	**-0.14**	**0.01**	**0.29**	**0.28**	0.00	**0.15**	**0.11**	**0.09**	**-0.11**	**0.20**	**-0.07**	**0.01**	**-0.06**	**0.09**	**0.38**		**-0.05**
(19)	*lnELAPSE*	**-0.01**	**-0.01**	**0.10**	0.00	**0.05**	**0.01**	**-0.09**	**0.02**	**-0.14**	**-0.36**	**0.14**	**-0.30**	**-0.11**	**-0.01**	**0.02**	**-0.01**	**-0.08**	**-0.05**	

(*continued on next page*)

Table 6 Panel (B) (continued)

Pharma only

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1)	*BOLD*		**-0.03**	**-0.06**	**0.02**	**-0.02**	**-0.02**	-0.01	**0.02**	**0.04**	**0.02**	**-0.04**	**0.03**	0.01	**0.01**	**-0.02**	0.01	**0.01**	**0.01**	0.00
(2)	*MATCH*	**-0.03**		**0.28**	0.00	**0.02**	**0.05**	**0.04**	**-0.13**	**-0.16**	**0.03**	**0.14**	**-0.06**	**0.06**	**-0.10**	**0.03**	**0.03**	**-0.08**	**-0.20**	-0.01
(3)	*RD*	**-0.06**	**0.26**		**-0.01**	**0.16**	**0.08**	**-0.19**	**-0.13**	**-0.49**	**-0.17**	**0.44**	**-0.33**	**-0.07**	**-0.22**	**0.03**	**-0.07**	**-0.14**	**-0.09**	**0.10**
(4)	*lnPACY*	**0.01**	**-0.02**	**-0.02**		0.00	**0.05**	**0.05**	**-0.03**	**0.02**	0.01	**-0.03**	**0.02**	0.00	**0.02**	**0.01**	**0.03**	**0.05**	**-0.01**	0.00
(5)	*lnNUMCOM*	**-0.01**	**0.03**	**0.17**	**0.09**		**0.76**	**-0.11**	**0.33**	**-0.14**	**-0.13**	**0.20**	**-0.16**	**-0.10**	**-0.07**	**0.03**	**-0.02**	**0.09**	**0.22**	**0.07**
(6)	*lnNFORE_T*	**-0.02**	**0.04**	**0.06**	**0.16**	**0.78**		**0.25**	**0.18**	**-0.01**	**0.01**	**0.05**	**0.02**	**-0.06**	**-0.02**	**0.03**	**0.19**	**0.17**	**0.24**	**0.04**
(7)	*lnNFORE_F*	**-0.01**	**0.03**	**-0.21**	**0.07**	**-0.11**	**0.30**		**-0.12**	**0.26**	**0.32**	**-0.23**	**0.35**	**0.15**	**0.03**	**0.06**	**0.21**	**0.21**	0.01	**-0.09**
(8)	*lnNUMIND*	**0.02**	**-0.16**	**-0.13**	0.00	**0.37**	**0.22**	**-0.10**		**-0.03**	**-0.15**	**0.03**	**-0.16**	**0.05**	**0.01**	0.00	**-0.08**	**0.01**	**-0.03**	**0.06**
(9)	*INTA*	**0.04**	**-0.14**	**-0.44**	**0.02**	**-0.10**	**0.02**	**0.24**	**-0.03**		**0.39**	**-0.55**	**0.57**	**0.04**	**0.29**	**-0.04**	**0.12**	**0.19**	**0.13**	**-0.16**
(10)	*lnAF*	**0.01**	**0.03**	**-0.18**	**0.02**	**-0.10**	**0.03**	**0.25**	**-0.17**	**0.33**		**-0.53**	**0.77**	**0.35**	**-0.03**	**-0.08**	**0.22**	**0.31**	**0.08**	**-0.34**
(11)	*RETVOL*	**-0.03**	**0.10**	**0.29**	**-0.02**	**0.12**	**0.02**	**-0.16**	**0.03**	**-0.30**	**-0.35**		**-0.72**	**-0.18**	**-0.15**	**0.09**	**-0.19**	**-0.30**	**-0.13**	**0.20**
(12)	*lnMCAP*	**0.03**	**-0.06**	**-0.35**	**0.03**	**-0.15**	**0.03**	**0.32**	**-0.17**	**0.51**	**0.73**	**-0.47**		**0.16**	**-0.03**	**-0.10**	**0.26**	**0.34**	**0.18**	**-0.29**
(13)	*INST*	**0.01**	**0.05**	**-0.08**	0.00	**-0.10**	**-0.06**	**0.11**	**0.03**	**-0.03**	**0.38**	**-0.15**	**0.15**		**-0.13**	**-0.03**	**0.04**	**0.10**	**-0.11**	**-0.13**
(14)	*BM*	0.00	**-0.07**	**-0.12**	0.01	**-0.05**	**-0.01**	**0.03**	**-0.01**	**0.19**	**-0.03**	**-0.06**	**0.01**	**-0.07**		**0.01**	**0.02**	0.00	**0.02**	**-0.01**
(15)	*lnBRO*	**-0.02**	**0.02**	**0.02**	**0.02**	**0.03**	**0.03**	**0.06**	0.00	**-0.03**	**-0.06**	**0.05**	**-0.08**	**-0.02**	0.00		**-0.02**	**-0.07**	**-0.04**	**0.04**
(16)	*lnHOR*	0.01	**0.02**	**-0.06**	**0.07**	**-0.02**	**0.19**	**0.21**	**-0.12**	**0.11**	**0.22**	**-0.13**	**0.26**	**0.05**	0.00	**-0.02**		**0.08**	**0.08**	0.00
(17)	*lnFEXP*	0.01	**-0.08**	**-0.15**	**0.10**	**0.09**	**0.18**	**0.20**	0.00	**0.14**	**0.29**	**-0.21**	**0.33**	**0.09**	**-0.01**	**-0.06**	**0.08**		**0.35**	**-0.10**
(18)	*lnGEXP*	0.01	**-0.18**	**-0.09**	**0.02**	**0.26**	**0.26**	0.00	**-0.01**	**0.11**	**0.07**	**-0.08**	**0.18**	**-0.09**	0.00	**-0.05**	**0.10**	**0.35**		**-0.03**
(19)	*lnELAPSE*	0.00	-0.01	**0.12**	0.00	**0.07**	**0.03**	**-0.11**	**0.07**	**-0.17**	**-0.37**	**0.14**	**-0.31**	**-0.13**	**-0.02**	**0.02**	**-0.01**	**-0.09**	**0.03**	

Panel (C): Regression results - Full sample

	All forecasts		Last forecasts		Forecasts after EA	
	i	ii	iii	iv	v	vi
RD	-0.515***	-0.671***	-0.538***	-0.641***	-0.597***	-0.720***
	(0.047)	(0.091)	(0.084)	(0.128)	(0.060)	(0.115)
MATCH		-0.122***		-0.092		-0.096*
		(0.047)		(0.071)		(0.055)
MATCH × RD		0.235**		0.168		0.184
		(0.101)		(0.141)		(0.122)
lnPACY	0.096***	0.098***	0.097*	0.104**	0.100**	0.117***
	(0.032)	(0.033)	(0.051)	(0.051)	(0.044)	(0.044)
lnNUMCOM	0.040	0.038	-0.054	-0.053	0.033	0.031
	(0.055)	(0.056)	(0.093)	(0.094)	(0.074)	(0.075)
lnNFORE_T	-0.030	-0.020	0.065	0.063	-0.052	-0.050
	(0.046)	(0.047)	(0.073)	(0.073)	(0.057)	(0.059)
lnNFORE_F	-0.113***	-0.107***	0.115**	0.132**	0.007	0.021
	(0.035)	(0.036)	(0.056)	(0.056)	(0.037)	(0.038)
lnNUMIND	0.011	-0.005	-0.046	-0.059	0.012	-0.001
	(0.029)	(0.029)	(0.043)	(0.043)	(0.035)	(0.035)
INTA	0.096	0.102	0.199*	0.203*	0.104	0.103
	(0.065)	(0.065)	(0.111)	(0.111)	(0.085)	(0.085)
lnAF	-0.087***	-0.080***	-0.083*	-0.080	-0.082**	-0.076**
	(0.028)	(0.029)	(0.050)	(0.050)	(0.037)	(0.037)
RETVOL	-0.064	0.045	0.363	0.450	-0.047	0.026
	(0.380)	(0.380)	(0.715)	(0.725)	(0.468)	(0.475)
lnMCAP	0.023**	0.023**	0.044***	0.044***	0.066***	0.065***
	(0.009)	(0.009)	(0.015)	(0.015)	(0.012)	(0.012)
INST	0.085*	0.078	0.174*	0.150*	0.098	0.092
	(0.048)	(0.048)	(0.090)	(0.091)	(0.060)	(0.060)
BM	-0.029	-0.031	-0.066*	-0.069*	-0.058*	-0.059*
	(0.025)	(0.025)	(0.036)	(0.036)	(0.032)	(0.032)
lnHOR	-0.041**	-0.041**	0.123***	0.129***	-0.136***	-0.135***
	(0.021)	(0.021)	(0.045)	(0.045)	(0.031)	(0.031)
lnBRO	0.020	0.014	0.031	0.025	0.011	0.004
	(0.014)	(0.015)	(0.020)	(0.021)	(0.013)	(0.014)
lnFEXP	0.002	0.002	-0.043***	-0.040**	-0.027**	-0.027**
	(0.009)	(0.009)	(0.016)	(0.016)	(0.011)	(0.011)
lnGEXP	0.022	0.020	0.013	0.012	0.019	0.018
	(0.014)	(0.014)	(0.023)	(0.023)	(0.016)	(0.016)
lnELAPSE	-0.003	-0.004	0.031***	0.030***	0.066***	0.064***
	(0.008)	(0.008)	(0.011)	(0.012)	(0.008)	(0.008)
Observations	75707	74294	19202	18753	46392	45555
Pseudo R2	0.0129	0.0132	0.0258	0.0257	0.0198	0.0199
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel (D): Regression results - Pharma only

	All forecasts		Last forecasts		Forecasts after EA	
	i	ii	iii	iv	v	vi
RD	-0.492***	-0.760***	-0.507***	-0.756***	-0.548***	-0.827***
	(0.048)	(0.098)	(0.085)	(0.136)	(0.060)	(0.125)
MATCH		-0.223***		-0.234***		-0.239***
		(0.053)		(0.083)		(0.066)
MATCH × *RD*		0.401***		0.394***		0.415***
		(0.107)		(0.150)		(0.136)
lnPACY	0.092**	0.098***	0.065	0.087	0.106**	0.123**
	(0.036)	(0.038)	(0.057)	(0.057)	(0.050)	(0.049)
lnNUMCOM	0.068	0.083	0.011	0.032	0.059	0.067
	(0.057)	(0.059)	(0.102)	(0.103)	(0.083)	(0.083)
lnNFORE_T	-0.054	-0.051	0.042	0.033	-0.043	-0.037
	(0.048)	(0.049)	(0.084)	(0.084)	(0.067)	(0.067)
lnNFORE_F	-0.120***	-0.111***	0.134**	0.156**	0.017	0.029
	(0.039)	(0.039)	(0.064)	(0.064)	(0.042)	(0.042)
lnNUMIND	0.006	-0.019	-0.076*	-0.095**	0.013	-0.010
	(0.030)	(0.030)	(0.044)	(0.044)	(0.036)	(0.037)
INTA	0.153**	0.148**	0.220*	0.211*	0.200**	0.181**
	(0.069)	(0.068)	(0.121)	(0.122)	(0.090)	(0.090)
lnAF	-0.058*	-0.052*	-0.067	-0.063	-0.062	-0.054
	(0.030)	(0.031)	(0.055)	(0.055)	(0.041)	(0.041)
RETVOL	-0.014	0.107	0.121	0.211	-0.058	0.024
	(0.393)	(0.392)	(0.728)	(0.738)	(0.487)	(0.493)
lnMCAP	0.030***	0.030***	0.056***	0.056***	0.075***	0.074***
	(0.010)	(0.010)	(0.016)	(0.016)	(0.013)	(0.013)
INST	0.025	0.024	0.149	0.141	0.034	0.029
	(0.052)	(0.052)	(0.099)	(0.100)	(0.065)	(0.065)
BM	-0.031	-0.031	-0.056	-0.057	-0.068**	-0.070**
	(0.025)	(0.025)	(0.036)	(0.036)	(0.032)	(0.033)
lnHOR	-0.041*	-0.038	0.109**	0.125**	-0.185***	-0.181***
	(0.024)	(0.024)	(0.049)	(0.049)	(0.035)	(0.036)
lnBRO	0.005	0.002	-0.018	-0.021	-0.015	-0.018
	(0.013)	(0.013)	(0.023)	(0.023)	(0.016)	(0.017)
lnFEXP	-0.001	-0.002	-0.043**	-0.044**	-0.030**	-0.030**
	(0.010)	(0.010)	(0.018)	(0.018)	(0.012)	(0.012)
lnGEXP	0.011	0.005	-0.004	-0.007	0.004	-0.002
	(0.015)	(0.016)	(0.025)	(0.026)	(0.017)	(0.018)
lnELAPSE	0.013	0.012	0.047***	0.045***	0.075***	0.074***
	(0.008)	(0.008)	(0.012)	(0.013)	(0.009)	(0.009)
Observations	55129	54542	14570	14370	34960	34960
Pseudo R2	0.008	0.008	0.015	0.016	0.015	0.015
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

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