The impact of separating sell-side research payments from dealing commissions: Evidence from Sweden

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Abstract

Sell-side investment research has traditionally been an important source of non-price competition between investment banks with whom institutional investors trade. Economic theory predicts that non-price competition leads suppliers to overproduce non-priced services. We study the impact on sell-side research and stock market reaction of separating research payments from dealing commissions when Sweden's largest asset managers required sell-side firms to separate research payments and dealing commissions using the research payment account (RPA) model. Using a hand-collected dataset revealing analyst location, we find that introduction of the RPA model coincides with a reduction in the supply of sell-side research – on average analyst coverage falls. The reduction in coverage is greater for smaller firms, those with less institutional investors, and those not included in the benchmark index. We also find that the RPA model is associated with an overall improvement in analysts' research quality, as evidenced by superior earnings forecast accuracy and stronger market reaction to forecast revisions in the post-RPA adoption period. Overall, our results suggest that unbundling research payments is associated with an improvement in the information environment for firms with analyst coverage, even though some firms suffer a reduction in analyst coverage.

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1. Introduction

Institutional investors have traditionally paid sell-side brokerage firms using bundled payments covering research services and trade execution fees. The bundled payments model facilitates non-price competition between sell-side firms – research services are not priced but are used to attract institutional brokerage business. The bundled payments model has potential adverse consequences for asset owners who might overpay for sell-side services, to the detriment of investment performance. The inefficiencies associated with the bundled research payments system have been the subject of a length policy debate in the European Union, culminating in January 2018 with the issuance of the revised *Markets in Financial Instruments Directive* (MiFID II). From 2018, MiFID II requires asset managers to pay sell-side firms for research services either from their own funds or through a research payment account (RPA) funded by transparent charges to asset owners. However, three years earlier in 2015, the largest investment managers in Sweden pre-empted MiFID II regulation by voluntarily introducing an RPA regime. We study the effects of this unregulated asset manager-driven implementation of unbundled research payments in Sweden on the supply of research services (analyst coverage), the quality of research (forecast accuracy) and the market consequences (market reaction to forecast revisions).

Spence (1977) shows that, in equilibrium, non-price competition can lead a competitive industry to over-produce non-priced services and encourages excessive numbers of industry entrants. Consistent with this theory, opaque soft dollar payments for sell-side research may encourage over-production of sell-side research, subsidized by excessive bundled brokerage fees paid by asset managers. On the supply side, when they are not held accountable for the profitability of their research, sell-side research departments and their analysts may offer inefficient "waterfront coverage" of companies to solicit business from asset managers.[1] Hence profit-maximizing brokerages forced to unbundle charges for research services will have incentives to better control the costs of research, and to adjust the supply of research in response to demand from asset managers. They will also have incentives to improve the quality of research if asset managers are willing to pay more for higher quality research. Based on this view that under the bundled payments model sell-side research is a source of non-price competition, we predict and find that the requirement to unbundle research payments from execution fees leads Swedish sell-side firms to reduce analyst coverage, especially of smaller companies with fewer institutional investors. At the same time, we predict and find that the quality of research improves after fee unbundling.

Both domestic and foreign analysts conduct research on larger companies considered investible by institutional investors. We expect that the introduction of RPA in Sweden will have greatest impact on domestic sell-side research in Sweden because foreign analysts are less likely to be subject the RPA model introduced by Swedish investment managers prior to the broader implementation of MiFID II. Hence we use a difference-in-differences research design to study the supply of sell-side research by analysts working in Sweden, using foreign analysts as a control group. To increase the power of our tests we focus only on research relating to companies listed in Sweden. We hand-collect from social media the geographical locations of 1,067 analysts covering Swedish listed companies. Our sample comprises 263 analysts based in Sweden (the treatment group) and 800 (688) analysts based in other countries (other EU countries) (the control groups).[2]

[1] See, e.g., Edison Investment Research 2013.
[2] There are fourteen analysts relocated internationally, among which four analysts used to be in Sweden. We delete these four analysts that used to reside in Sweden but relocated to other countries from the treatment group.

Overall, our research indicates that analyst coverage depends on the transparency of payments for sell-side research. More transparent pricing of research services is associated with reduced supply of research, especially where demand for research is lower. We find that after the adoption of RPA in Sweden, coverage of Swedish companies by Swedish analysts falls relative to non-Swedish analysts by an average of 0.62 companies. Then, focusing on companies listed on Nasdaq OMX Stockholm, the largest Swedish stock market, we find that Swedish analysts reduce coverage primarily for lower market capitalization companies with fewer institutional investors, and for companies that are not included in the Benchmark index.[3] These results are consistent with an oversupply of research when it is treated as an unpriced service.

Our results also suggest research payments transparency is associated with an improvement in the quality of domestic sell-side research. Using analyst forecast accuracy as a proxy for research quality, our results show that the accuracy of Swedish analysts' forecasts increases after the introduction of the RPA model. Moreover, the increase in forecast accuracy is due to an improvement in analysts' forecasting performance, and is not due to a reduction in coverage by lower quality analysts. Finally, we find that the market reaction to Swedish analysts' forecast revisions increases by 42% on average after RPA adoption, with the increase being considerably larger for smaller companies.

Our paper contributes to the literature in three main ways. First it builds on prior research focusing on the role of compensation channels in determining analysts' coverage decisions and the quality of analysts' research. The extant literature concentrates on analysts' incentives arising through two compensation channels supported by opacity in the pricing of sell-side research: interdependencies between sell-side research and the investment banking function

[3] The Benchmark index refers to Nasdaq OMX Stockholm Benchmark index, which is the major index in Sweden. The Benchmark index comprises only large and liquid stocks.

(e.g., Lin and McNichols 1998; Michaely and Womack 1999; Dechow et al. 2000; O'Brien et al. 2005); and the dependence of sell-side research resources on dealing commissions, and hence trading volume (e.g., Cowen et al. 2006; Hayes 1998; Irvine 2000; Irvine 2004; Jackson 2005). Our setting allows us to study analysts' coverage decisions and research quality when revenue generated by sell-side research is made transparent within the sell-side brokerage house. Our evidence is consistent with transparency of research payments mitigating incentives to over-supply lower quality research.

Our paper also contributes to the literature on cross-sectional differences in companies' information environments and the stock market effects of analysts' research. Analyst coverage is often used as proxy for quality of the information environment. We find that the transparency shock to research payments has a direct impact on analyst coverage, reducing the supply of research for smaller, less liquid companies with less institutional investors. However, our results do not suggest a detrimental on companies' information environments because the quality of analysts' forecasts and their stock market effects increase.

Our research is also relevant to policy makers. It provides early evidence that the changes subsequently introduced under MiFID II have consequences for the supply and quality of sell-side research. MiFID II was mandated in January 2018.[4] However, the regulatory change appears to have had direct consequences on the availability of analyst detail data as data vendors and sell-side firms seek to monetize sell-side research. This potentially undermines opportunities for researchers to investigate the direct consequences MiFID II.[5]

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[4] Available at: https://www.esma.europa.eu/policy-rules/mifid-ii-and-mifir. [Accessed: 20 August 2017]
[5] The sell-side analyst research database – I/B/E/S – anonymized analysts' identity completely since October 18, 2018. Available at: https://wrds-www.wharton.upenn.edu/documents/1030/Product_Change_Notification-IBES_Detail_History-_PreApproval_Contributor.._.pdf?_ga=2.261353929.537725635.1561558633-1536111742.1484332703. [Accessed: 12 March 2019]

In the remainder of the paper we proceed 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 3, we outline the research design. Section 4 presents the various sources of data and gives a general description of the Swedish market. Section 5 reports the primary results and findings. Section 6 concludes.

2. Background, literature review, and hypothesis development

2.1 Background

Traditionally payments by asset managers for sell-side research services including software, hardware, database access and research reports have been bundled with trading execution fees. Effectively payments for research services are linked to trading volume but are not made explicit. Figure 1 illustrates the bundled payments model. Panel (A) represents the model where asset manager preferences play no direct role in compensating for research, beyond choosing to execute trading with a brokerage house. The dealing commission is calculated as the trading value multiplied by a fixed rate negotiated between asset managers and brokers. Having received the dealing commission, brokerage houses split and distributes the commission proportionately to the research department where sell-side analysts work and the trading department.[6] 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.

More recently, asset managers have been given greater influence over the flow of commissions to broker firm research departments than a pure bundled fee model suggests. The

[6] 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.

use of *Client Commission Arrangements* in the US or similarly *Commission Sharing Agreements* in Europe.[7, 8] Figure 1, Panel (B) illustrates such arrangements. Under the CSA and CSA, asset managers establish an account with their brokers holding a proportion of the dealing commission for research services. The broker manages the account and distributes research service payments to all qualifying sell-side research providers based on asset managers' "broker votes." Asset managers hence can indirectly affect the payments to the research departments of different brokerage firms based on the ex post perceived quality of the research. However, the payments for research are not explicitly associated with consumption of research services. Research services therefore still retain the characteristics of non-priced services.

Under the Research Payments Account model, the precise amounts of research payments and trading execution fees, are presented separately to investors. Panel (C) of Figure 1 illustrates the RPA model. Dealing commission and the soft dollar arrangements disappear under the RPA model and the link between research payments and the trading volume is eliminated. Alternatively, asset managers can choose to bear the cost of research services on their own profit and loss account. Whether asset managers self-finance or use RPA to pay for the research services consumed, the price of those services is made explicit. Proponents of RPA argue that this will radically curb asset managers' overspending on research services and reduce fees for investors.

Bundled payments and associated soft dollar payments for non-priced research services are controversial. Advocates argue that soft dollars are an innovative and efficient form of economic organization capable of benefiting investors by supporting asset managers' search

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[7] 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]

[8] 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]

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 fee model can mitigate agency problems inherent in delegated portfolio management. This view is implicitly endorsed by the SEC in Section 28(e) of the Securities Exchange Act 1934 (the Safe Harbor Rule) permitting soft dollar payments. Furthermore, Brennan and Chordia (1993) argue that brokerage commissions linked to informed trading volume could be an efficient alternative to explicit charging for research based on signal realizations.

In contrast, opponents of fee bundling argue that asset managers may abuse the opacity of soft dollars by over-consuming research or consuming perquisites provided through brokerage firms to unjustly enrich themselves, leading to inefficient use of asset owners' resources (Blume 1993, Bolge 2009, Erzurumlu and Kotomin 2016). Specifically, asset managers may treat sell-side research services as a "free good" because they do not bear the cost of consuming such service. Hence research services are non-priced products. Within a competitive industry like sell-side research services, brokerage houses may over-produce such non-priced services, perhaps using them as "advertising" tools to solicit business from asset managers. Given that the exact amount spent on research is unknown to investors, asset managers may prioritize research services in the selection of trading execution services provided by brokerage houses (Myners 2001).[9]

Empirical evidence on the effects of sell-side research payment methods is scarce, primarily because changes in payment methods have been rare. A few studies have examined

[9] 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]

the links between soft dollar arrangements and returns to investors. For example, in a recent paper examining actual 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 a similar spirit, Edelen et al. (2012) compare the returns of funds where distribution costs are either bundled with brokerage commissions (relatively opaque) or expensed from funds' income statements (relatively transparent), finding that opacity of distribution costs is associated with significantly more negative returns. Although Edelen et al. (2012) focus on distribution costs, not research payments, their results indicate that opacity of brokerage commissions is associated with the poorer performance.

In this paper we take a different perspective. We examine the supply side of brokerage research and the effects of a shock to the pricing model, introduced by buy-side investors. We focus on whether the introduction of pricing for research services affects the supply and quality of research services offered by brokerage firms. In 2015, some of the largest Swedish asset management companies, including Swedbank Robur, SEB and Svenska Handelsbanken, announced that they would require the unbundling of research payments from execution costs.[10] These three asset management companies account for over 50% of the assets under management in the Swedish asset management market.[11] [12] Their adoption of RPA provides an

[10] 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 4 presents more details.

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

[12] The possible reason that we have the largest asset managers switching to the unbundled payment model is that 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

opportunity to study the impact of an unregulated RPA adoption on Swedish sell-side analysts and on the Swedish stock market as the early evidence to the influence of separating research payments from the dealing commission.[13] [14]

2.2 Hypothesis 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 would lead 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 affect analysts' coverage decision and their research quality, as well as firms' information environment.

(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 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

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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.

[13] 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.

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

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.[15] 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

[15] ' …[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]

asset managers. Turning to the 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 the number of firms' institutional investors as the direct measure of firms' attractiveness to asset managers. Then we expect that firms with less institutional investors 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.[16] 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 2: After the RPA adoption, the decrease in the number of analysts is greater among the firms whose research are less attractive to asset managers.

(C) Analysts' research quality

[16] 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. 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. We use forecast accuracy as the proxy to test the improvement in research quality.[17] 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 managers.[18] 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

[17] We use forecast accuracy and forecast error interchangeably. High forecast accuracy means low forecast error.
[18] Brown et al. (2015): page 31-34, Table 10.

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 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.

2.3 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 separating research payment is to enhance the efficiency of asset managers using the research budget 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 model when they access the international market.[19] Figure 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 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,

[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.
[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.

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 majority of firms in the treatment group are different to firms in the control group.

3. Research design

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 either the number of firms followed by each individual analyst within a year (*NUMFIRM*), or the natural logarithm form of *NUMFIRM* (*Ln(NUMFIRM)*). 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 for the years of 2013 and 2014. 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 (*Ln(GEXP)*), defined as the number of years in the natural logarithm form since the analyst provided her first forecast for any firm; and analysts' industry coverage (*Ln(NUMIND)*), defined as the number of industries in the natural logarithm form followed by each analyst.[21] Secondly, Groysberg et al. (2011) find that analysts' forecast error is positively associated with their employment turnover. In

[21] 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.

other words, analysts that cannot provide accurate forecasts have a higher chance of being fired. In an attempt to control for the ability of analysts' past accuracy (*Ln(PACY)*), we follow 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:

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

$$PACY_{jt} = \frac{1}{n}\sum_{i}^{n} Percentile\ Rank_{ijt-1} \tag{2}$$

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*. AF_{it-1} is the number of analysts following firm *i* in year *t-1*. $PACY_{jt}$ is the analyst *j*'s average accuracy scores for all the firms she covers in year *t-1*. The we turn $PACY_{jt}$ into the natural logarithm form. Lastly, we also control for the analyst and year fixed effects (*FE*) in different specifications to account for the analysts and time unobservable invariants. The regression is as follows:

$$\begin{aligned} &Ln(NUMFIRM_{jt})\ or\ NUMFIRM_{jt} \\ &\quad = \alpha_0 + \alpha_1 RPA_t + \alpha_2 SW_j + \alpha_3 RPA_t \times SW_j + \alpha_4 Ln(GEXP_{jt}) \\ &\quad + \alpha_5 Ln(NUMIND_{jt}) + \alpha_6 Ln(PACY_{jt}) + FE + \varepsilon_{jt} \end{aligned} \tag{3}$$

3.2 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-year (*j, t*) to firm-year (*i, t*). This firm-year unit of data structure allows us to incorporate firms' feature into the regression. We focus only on firms listed on Nasdaq OMX Stockholm (the largest Swedish market) 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.[22]

We use the Ordinary Least Square regression (OLS) to test Hypothesis 2. The dependent variable is the number of Swedish analysts following each firm (*SW_AF*). The indicator variable *RPA* is the variable of interest as defined previously. Next, we define four dummy variables (***LESSDEMAND***) as the proxy for firms whose research are less demanded. First, we define two dummy variables for small firms (*SMALLMED* and *SMALLIND*). *SMALLMED* is the dummy variable for small firms with the value of one if a firm has the market value of equity less than the median value of all firms in the end of the previous year, and zero otherwise. *SMALLIND* is the dummy variable for firms that are included in Nasdaq OMX Stockholm Small-cap index within a year, and zero otherwise.[23] In a similar vein, we define the dummy variable of *LOWNUMINST* as the firm with less institutional investors, set the value to one if the number of a firm's institutional investors is less than the median value of all firms at end of the previous year, and zero otherwise. In addition, we define dummy variable *NONBENCH*, with the value of one, as the firm that are not included in the Nasdaq OMX Stockholm Benchmark index at the end of each previous year. Therefore, the vector ***LESSDEMAND*** contains *SMALLMED*, *SMALLIND*, *LOWNUMINST*, and *NONBENCH*. We interact

[22] 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 following and have an aggregated market value of equity accounting for 99% among the five markets at the end of 2013. The Swedish Financial Market Report (2014), page 55-56. Online available: http://archive.riksbank.se/Documents/Rapporter/Finansmarknaden/2014/rap_finansm_140829_eng.pdf [Accessed 21 May 2016]

[23] Nasdaq OMX Stockholm exchange have three size-based indices: Small-cap, Medium-cap, and Large-cap. The cutoff is based on the firms' market value in the November in previous year and become effective in indices as of the first trading day in January. Firms with a market value below 150 million Euros are in the small-cap index. Firms with a market value between 150 million and 1 billion Euros are contained within the Medium-cap index, while firms with a market value over 1 billion Euros are presented within the Large-cap index. Online available: https://indexes.nasdaqomx.com/docs/Methodology_NORDIC.pdf [Accessed 25 June 2019]

LESSDEMAND 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 (*Ln(MV)*), stock return volatility (*RETVOL*), 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 year fixed effects. The model is as follows:

$$
\begin{aligned}
SW\_AF_{it} = {} & \alpha_0 + \alpha_1 \boldsymbol{LESSDEMAND_{it}} + \alpha_2 RPA_t \times \boldsymbol{LESSDEMAND_{it}} \\
& + \alpha_3 Ln(MV)_{it} + \alpha_4 INTA_{it} + \alpha_5 MB_{it} + \alpha_6 INST_{it} \\
& + \alpha_7 RETVOL_{it} + FE + \varepsilon_{it}
\end{aligned} \tag{4}
$$

where ***LESSDEMAND*** *are SMALLMED*, *SMALLIND*, *LOWNUMINST*, and *NONBENCH*

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 year since 2014, and zero otherwise, we include interaction terms of ***LESSDEMAND*** with both *RPA* and *PRE* in the regressions (4), and expect no significance on the interaction terms of *PRE* × ***LESSDEMAND***.

$$
\begin{aligned}
SW\_AF_{it} = {} & \alpha_0 + \alpha_1 \boldsymbol{LESSDEMAND_{it}} + \alpha_2 RPA_t \times \boldsymbol{LESSDEMAND_{it}} \\
& + \alpha_3 PRE_t \times \boldsymbol{LESSDEMAND_{it}} + \alpha_4 Ln(MV)_{it} + \alpha_5 INTA_{it} \\
& + \alpha_6 MB_{it} + \alpha_7 INST_{it} + \alpha_8 RETVOL_{it} + FE + \varepsilon_{it}
\end{aligned} \tag{5}
$$

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 one-year-ahead 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 year (*i, j, t*). Two indicator variables, *RPA* and *SW*, are as previously defined. Then the interaction term *RPA* × *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. Firstly, in line with Clement (1999) and Mikhail et al. (1997), we control for firm-specific experience (*Ln(FEXP)*), general experience (*Ln(GEXP)*), the number of firms covered (*Ln(NUMFIRM)*) and the number of industries followed (*Ln(NUMIND)*) by each individual analyst. Secondly, in an attempt to measure an individual analyst's past forecast ability, we use the past accuracy score (*Ln(PACY)*) again. The last analyst-related control variable is forecast horizon (*Ln(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 (*Ln(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*), as well as a dummy variable for firms with negative net income figures (Alford and Berger, 1999; Brown, 1997; Brown, 2001; Hwang et al.,1996; Sinha et al., 1997 etc.). Lastly, we include firm, year, and analyst fixed effects (*FE*) in different specifications to control for invariant factors. Based on the above discussion, we have the following research design:

$$FORERR_{ijt} = \alpha_0 + \alpha_1 RPA_t + \alpha_2 SW_j + \alpha_3 RPA_t \times SW_j + \boldsymbol{\beta CONTROL_A} + \boldsymbol{\gamma CONTROL_F} + FE + \varepsilon_{ijt} \quad (6)$$

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

- $Ln(GEXP_{jt})$, $Ln(FEXP_{ijt})$, $Ln(NUMIND_{jt})$, $Ln(NUMFIRM_{jt})$, $Ln(PACY_{jt})$, and $Ln(HOR_{ijt})$

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

- $Ln(MV_{it})$, $INTA_{it}$, MB_{it}, $INST_{it}$, $RETVOL_{it}$, and $LOSS_{it}$

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.

$$PR\left(DIS_{ijt} = 1\right) = \alpha_0 + \alpha_1 SW_j + \alpha_2 FORERR_{ijt} + \alpha_3 SW_j \times FORERR_{ijt} + \boldsymbol{\beta CONTROL_A} + \boldsymbol{\gamma CONTROL_F} + FE + \varepsilon_{ijt} \quad (7)$$

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 firms listed on the Nasdaq OMX Stockholm and 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 year-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. 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.[24] We replicate this step for the medium-cap firms and the small-cap firms respectively. The variable of interest is *RPA* as defined previously. We define ***ANADAY*** as a set of dummy variables for the two-day [0, +1] window when analysts revise their quarter or annual earnings forecasts for a firm. ***ANADAY*** includes any analysts (*ANA*), Swedish analysts (*ANASW*), and non-Swedish foreign analysts (*ANAFORE*). We interact ***ANADAY*** with *RPA*, and expect a positive coefficient on the interaction term with Swedish analysts only, as well as an insignificant coefficient on the interaction term with foreign analysts. 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 control for firm times year fixed effects and day fixed effect (*FE*). In addition. We partition the sample into the large-cap firms, medium-cap firms, and small-cap firms based on the constituents of Nasdaq OMX Large-cap, Medium-cap, and Small-cap, and re-run the regression.

[24] The large-cap index values are not available before May 21, 2013 on Bloomberg or DataStream. We replace the Nasdaq OMX Stockholm Benchmark index with the missing large-cap index value.

$$ABS\_ABRET_{it} = \alpha_0 + \boldsymbol{\alpha_1 ANADAY_{it}} + \boldsymbol{\alpha_2 ANADAY_{it}} \times RPA_t + \alpha_4 EARN_{it} + FE + \varepsilon_{it} \quad (8)$$

where $\boldsymbol{ANADAY_{it}}$ is either ANA_{it}, or both $ANASW_{it}$ and $ANAFORE_{it}$.

The regression is on the firm-day level and does not the analyst dimension, meaning that this setting has the same endogeneity issue as in 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 year since 2014, and zero otherwise, we include both the interaction term of $\boldsymbol{ANADAY}$ and both *PRA* and *PRE* in the regression.

$$ABS\_ABRET_{it} = \alpha_0 + \boldsymbol{\alpha_1 ANADAY_{it}} + \boldsymbol{\alpha_2 ANADAY_{it}} \times RPA_t + \boldsymbol{\alpha_3 ANADAY_{it}} \times PRE_t + \alpha_4 EARN_{it} + FE + \varepsilon_{it} \quad (9)$$

4. Data Collection

The sample period is from 2013 to 2016. Swedish analysts are the variable of interest. However, we do not have a straightforward database providing analysts' biographical and geographical information.[25] Therefore we hand-collected the data. The process of identification is in Appendix 2. We have identified 1,067 distinct analysts with their locations successfully. Table 1 Panel (B) reports analysts' geographical distribution.[26] The majority of analysts are from the UK (460 UK analysts), followed by 267 Swedish analysts, 62 analysts from Norway, 56 French analysts, 55 US analysts, and 52 Canadian analysts. Swedish analysts are the major party influenced by the RPA adoption in Sweden so that we use 263 Swedish analysts as the

[25] 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.
[26] Fourteen analysts relocated internationally during the sample period. Thus, the total number of analysts with the in Table 1 Panel (B) is 1,150. After subtracting the replicated 14 analysts, we have 1,136 distinct analysts.

treatment group and 800 non-Swedish analysts as the control group.[27] We also use 688 non-Swedish EU analysts as the alternative control group (Panel (C)). In addition, we collect analysts-related data from I/B/E/S, and accounting fundamentals from DataStream, as well as institutional ownership and the number of institutional investors from Bloomberg.

5. Empirical results

5.1 Results for analysts' firm coverage reduction

This section presents the results for Hypothesis 1, which is that the RPA adoption is associated with the reduction in the number of firms covered by analysts. Table 2, Panel (A) reports the descriptive statistics. Swedish analysts on average follow fewer firms and more industries, compared to the non-Swedish analysts. Panel (B) of Table 2 reports the results of the regressions with different specifications and with different control groups. Columns (i) to (iii) report the results with the dependent variable of the straightforward number of firms covered by analysts (*NUMFIRM*), whilst columns (iv) to (vi) report the results with the dependent variable of the logarithm form of *NUMFIRM*. 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. In particular, in column (ii), where we include analyst and year fixed effects, the estimated coefficient on the interaction term is -0.855, meaning Swedish analysts on average drop 0.855 more firms relative to non-Swedish analysts after RPA is adopted. In column (iii) where we use identified non-Swedish EU analysts as the control group, we find Swedish analysts drop 0.677 more firms relative to non-Swedish EU analysts. The results are similar when we use *Ln(NUMFIRM)* as the

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

dependent variable. With respect to other control variables, the number of industries *Ln(NUMIND)* is positively significant, indicating that analysts following more industries cover more companies. Next, we have positively significant coefficients on analysts' general experience (*Ln(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 (*Ln(PACY)*) has positive coefficients, consistent with the expectation that analysts with higher past accuracy are more likely to cover more firms. Overall, the results support Hypothesis 1. The RPA adoption by Swedish asset managers is associated with the reduction in the number of firms covered by the Swedish analysts.

5.2 Results for the type of firms being dropped

In this section, we report the results for Hypothesis 2, which is that the reduction in analyst following is greater for firms whose research are less demanded by institutional investors. We argue that small firms (*SMALLMED*, *SMALLIND*), firms with less institutional investors (*LOWNUMINST*), and firms that are not the Nasdaq OMX Benchmark index composite (*NONBENCH*) are firms with low institutional investor demand. We focus on Swedish analysts only and firms listed on the Nasdaq OMX Stockholm. During the sample period, 333 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 307. The remaining 26 firms are from other countries.[28]

Panel (A) of Table 4 reports the statistic description. Each firm is followed by around three Swedish analysts. Panel (B) presents the results for small firms while Panel (C) are for firms with less institutional investors and firms that are not included in the Benchmark index. The results are consistent with our expectation. Specifically, in column (ii), we have a significant

[28] For simplicity, we use "Swedish firms" to represent "333 firms listed on the Nasdaq OMX Stockholm" in the following sections.

coefficient of -0.492 on *RPA* × *SMALLMED*, meaning that small firms lose 0.492 more Swedish analysts compared to large firms after RPA was adopted, which is 38% of the mean of Swedish analysts following small firms before the RPA adoption.[29] The result is very similar when we use small-cap index to define small firms as shown in column (v).

Turning to the result of the test for firms with less institutional investors in columns (i) and (ii) of Panel (C), the negatively significant coefficient on *RPA* × *LOWNUMINST* suggests that the reduction in Swedish analyst following is greater among firms with less institutional investors with the RPA adoption in Sweden. Specifically, the coefficient on the interaction term in column (ii) is -0.39, which is 34% of the mean of Swedish analysts following firms with less institutional investors in the pre-RPA adoption period. Finally, we present the test results with firms' benchmark index partition in columns (iv) and (v) of Panel (C). We find a negatively significant coefficient on *RPA* × *NONBENCH*, 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 2014 onward, and zero otherwise, and we run the regression (5). The columns (iii) and (vi) in Panels (B) and (C) report the results. Consistent with our expectation, we only find the significant coefficients on the interaction term with *RPA*, rather than *PRE*, indicating that the selective reduction in Swedish 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

[29] The mean of Swedish analysts following small firms before 2015 is 1.31 (untabulated). The coefficient on the interaction term is -0.492, which is 38% of the mean (0.492/1.31=38%)

Swedish analyst following among small firms, firms with less institutional investors, as well as firms that are not included in the Benchmark index.

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, As we argued in Section 2.3 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. We present both results. Panel (A) of Table 5 shows the descriptive statistics of the variables used in the regression within the full sample. The average forecast error for Swedish analysts is 1.36%, compared to 1.42% for non-Swedish analysts. With the attrition of the data process, we have 2,294 firms, 213 Swedish analysts, and 751 non-Swedish analysts (including 658 non-Swedish EU analysts) in the final sample. Panel (B) of Table 5 reports the results of regressions with different specifications within the sample containing the entire firm coverage. 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. More precisely, in column (iii), where we control for analyst, firm and year fixed effects, the coefficient on the interaction term is -0.321, indicating that the forecast error of Swedish analysts decreased by 0.321% 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 1.66% (untabulated). The reduction in Swedish analysts' forecast error amounts to 19.3% of the mean of forecast error, compared to non-Swedish analysts.[30] When we use the identified EU analysts as the control group in column (iv), the results are

[30] The mean is 1.66%, then 0.321% / 1.66% = 19.3%.

qualitatively unchanged, which is -0.274 and significant at 1% level. Panel (D) in Table 5 reports the results within the sample that only contains firms covered by both Swedish analysts and non-Swedish analysts. We find 180 out of 2.294 firms covered both analysts within the same year. The sample size shrinks significantly. The observations drop from 111,526 to 35,412. The results are qualitatively unchanged, compared to that in Panel (B). After controlling for firm, analyst, and year fixed effects, we find that the coefficient on the interaction term is -0.283, 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 (v) of Panel (B) and Panel (D) in Table 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 (B) forecast error for Swedish analysts decreases by 0.344% 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 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.

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. Panel (A) of Table 7 reports data description. We have 321 unique firms in the final sample after deleting firms that miss stock price. We further partition the sample into small-cap group, medium-cap group, and large-cap group based on the constituents of Nasdaq OMX Stockholm small-cap index, medium-cap index, and large-cap index. Then we have 146 firms in the Small-cap group, 138 firms in the Medium-cap group, and 83 firms in the Large-cap group.[31] The *ABS_ABRET* is the size-adjusted daily absolute abnormal return. In Panel (A) of Table 7, firms from the small-cap group has a larger *ABS_ABRET* than firms from the large-cap group. The dummy variables *ANA*, *ANASW*, and *ANAFORE* are the 2-day window [0, +1] for days when any analysts, Swedish analysts, and non-Swedish (foreign) analysts revise their one-year-ahead EPS forecasts. Panel (A) of Table 7 shows that large-cap firms are in general receive more analysts' forecast revisions than the medium-cap firms and the small-cap firms.

Table 7, Pane (B) presents the results in different specifications for any analysts, regardless of their location. Columns (i) to (iv) report the regression results without adding pre-adoption dummies whilst columns (v) to (viii) are the results with pre-adoption dummies for the placebo tests. The results are largely consistent with our hypothesis. Specifically, in column (i), the estimated coefficient on *ANA* is 0.26 and significant at 1% level. This suggests that the daily market reaction to any analysts' forecast revisions is on average 0.26% higher than that without forecast revisions before the RPA adoption. In addition, we obtain a positively significant coefficient of 0.08 on *RPA* × *ANA*, indicating that the market reaction to forecast revisions increases by 31% in the post RPA period, relative to that in the pre-RPA period. After we partition the sample based on the firm size in columns (ii) to (iv), we continue finding a

[31] As Nasdaq OMX reconstructs the indices on the annual basis and based on firms' end-year market value of equity, some firms may be classified into different indices in different years. Thus, the sum of the numbers of unique firms from the Small-cap group, the Medium-cap group, and the Large-cap group are larger than the number of the unique firms in the "All firms" group.

positively significant coefficient on *RPA* × *ANA* for all different groups. As we argue that Swedish analysts are the major influenced party by the RPA adoption, compared to non-Swedish foreign analysts. We further decompose the analyst revision days (*ANA*) into Swedish analysts' revision days (*ANASW*) and the non-Swedish foreign analysts' revision days (*ANAFORE*). Then we replace *ANA* with *ANASW* and *ANAFORE,* and re-run the regression. We drop the firm-day observations when both Swedish analysts and non-Swedish analysts revise their forecasts for the same firm on the same day, in an attempt to reduce the impact of the overlapping revision. Panel (C) of Table 7 reports the results. We find that the coefficients on the interaction term between *RPA* and *ANASW* are deeply significant through all the sub-samples. This suggests an increase in the market reaction to Swedish analysts' forecast revisions in the post RPA adoption period. In contrast, we do not find any significant coefficients on the interaction term between *RPA* and *ANAFORE,* indicating that the market reaction to non-Swedish foreign analysts' forecasts remains unchanged in the post RPA period. Within each size-partitioned subsamples, we find that the increase in the market reaction to Swedish analysts' forecast revisions is the largest in the Small-cap group, compared to the Medium-cap group and the Large-cap group. Specifically, the coefficient for the *RPA* × *ANASW* in the Small-cap group (column ii) is 0.34, compared to 0.28 as the coefficient in the main variable *ANASW*, suggesting the increase in market reaction is more than 120%. With regard to the Medium-cap group and the Large-cap group (columns iii and iv), the increase in market reaction is only 33% and 53% respectively in the post period.

Columns (v) to (viii) of Panels (C) and (D) in table 7 report the placebo tests. Again, we introduce pre-adoption dummy *PRE*, and interact it with *ANA*, *ANASW*, and *ANAFORE*. We continue finding significant coefficients on the interaction term of *ANA*, *ANASW*, and *ANAFORE* 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. In Sum, we find evidence that the market reacts more strongly to Swedish analysts' forecast revisions in the post RPA adoption period. We do not find any increase in the market reaction to non-Swedish analysts' forecast revisions.

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. 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 less institutional investors 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 find an increase in market reaction to forecast revisions with the RPA adoption, in particular among smaller companies.

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 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. Third, 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.

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Appendix 1: Definition of variables

Firm-level variables		
Variable Name	Description	Source
ABS_ABRET	Size-adjusted absolute abnormal return in the percentage form.	DataStream Bloomberg
AF	The number of any analysts issuing one-year-ahead EPS forecasts within a year.	I/B/E/S
AF_SW	The number of Swedish analysts issuing one-year-ahead EPS forecasts within a year.	I/B/E/S
ANA	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.	I/B/E/S
ANASW	Dummy variable, with the value of one if a Swedish analyst provides forecast revisions on the day or the next day ([0, +1]), and zero otherwise.	I/B/E/S
ANAFORE	Dummy variable, with the value of one if a foreign (non-Swedish) analyst provides forecast revisions on the day or the next day ([0, +1]), 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 or the next day ([0, +1]), and zero otherwise.	I/B/E/S
INST	Percentage of institutional ownership.	Bloomberg
INTA	Intangible assets scaled by total assets	DataStream
LOSS	Dummy variable, set equal to one when actual EPS is negative, and zero otherwise.	I/B/E/S
LOWNUMINST	Dummy variable, set equal to one when the firm has the number of institutional owners lower than the median of all firms at the beginning of each year, and zero otherwise	DataStream
MB	Market value of equity divided by book value of equity.	DataStream
NONBENCH	Dummy variable, with a value of one if the firm is not included in the Nasdaq OMX Stockholm Benchmark index at the end of each previous year, and zero otherwise.	Bloomberg
Ln(MV)	Natural logarithm of the market value of equity.	DataStream
RETVOL	Standard deviation of daily stock returns within each year.	DataStream
RPA	Dummy variable. It equals to one when the observation is from the period after RPA is adopted, and zero otherwise.	
PRE	Dummy variable. It equals to one when the observation is from 2014 onwards, and zero otherwise.	
SMALLIND	Dummy variable, with the value of one when the firm is included in the Nasdaq OMX Stockholm Small-cap index, and zero otherwise.	Bloomberg
SMALLMED	Dummy variable, set equal to one when the market value of equity of the firm is less than median of all firms at the end of each previous year.	DataStream
OMX Small-Cap	Firms with a market value less than 150 million euros in the end of the previous year	Bloomberg
OMX Medium -Cap	Firms with a market value larger than 150 million euros but less than 1 billion euros in the end of the previous year	Bloomberg
OMX Large-Cap	Firms with a market value larger than 1 billion euros in the end of the previous year	Bloomberg

Analyst-level variables		
Variable Name	Description	Source
DIS	Dummy variable, set value of one if the analyst-firm pairs that disappeared in the post RPA adoption period, and zero otherwise.	I/B/E/S
Ln(FEXP)	Firm-specific experience in the natural logarithm form. Firm-specific experience is measured as the number of years from the analyst's first opinion on the specific firm to the 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 at the beginning of the fiscal year, then times 100.	I/B/E/S
Ln(GEXP)	General experience in the natural logarithm form. Analysts' general experience is measured as the number of years from the analyst's first opinion on any firm to the present.	I/B/E/S
Ln(HOR)	Forecast horizon in the natural 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
Ln(NUMFIRM)	Total number of firms covered by an analyst within each year in the natural logarithm form.	I/B/E/S
Ln(NUMIND)	Total number of industries (two-digit SIC codes) covered by an analyst within each year in the natural logarithm form.	I/B/E/S
Ln(PACY)	Analyst relative accuracy score in the previous year in the natural logarithm form, 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

Appendix 2: Identification of analysts' location

This appendix provides the details of identifying Swedish analysts and non-Swedish analysts. The Sample period is from 2013 to 2016. The identifying steps are as follows and Table 1 Panel (A) reports the process of identification:

1) We assume that the majority of Swedish analysts would follow firms that are listed on Swedish stock markets. The largest Swedish exchange is Nasdaq OMX Stockholm. We firstly collect all firms listed on Nasdaq OMX Stockholm from Bloomberg during the period from 2013 to 2016. In an attempt to obtain the time series of the OMX listed firms, we download the constituents of Nasdaq OMX Stockholm All-Share index in the year end from 2013 to 2016.[32] Then we obtain 379 unique shares. After deleting preference shares and special depositary receipts (SDR), we have 333 unique firms listed on Nasdaq OMX Stockholm.
2) We search for the I/B/E/S tickers in DataStream with the ISIN codes of these 333 firms, and obtain 331 unique I/B/E/S tickers. Two firms without I/B/E/S tickers are deleted.
3) Using these 331 I/B/E/S 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 analyst codes, surnames, initials of their first names and the abbreviations of their brokerage houses.[33] Then we obtain 1,136 unique analysts' codes.
4) Then we manually match analysts' biographical information and their I/B/E/S firm coverage lists with that in Bloomberg which provides analysts' full names and their firm coverage portfolio. More importantly, Bloomberg also provides analysts' locations, which enables us to create the treatment group;
5) 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).[34] 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. Hence, we have identified 1,067 distinct analysts with their locations successfully.

[32] 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 manually identify the annual index composite from Bloomberg.

[33] I/B/E/S used to store analysts' biographical information in the Recommendation file and the Target Price file. But they anonymize 40% of analysts' information since October 2018. Identifying analysts' biographical information becomes difficult afterwards. We have completed our analysts' identification in 2017 so that the I/B/E/S anonymization does not affect our sample.

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

Appendix 3: 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.

Appendix 4: 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

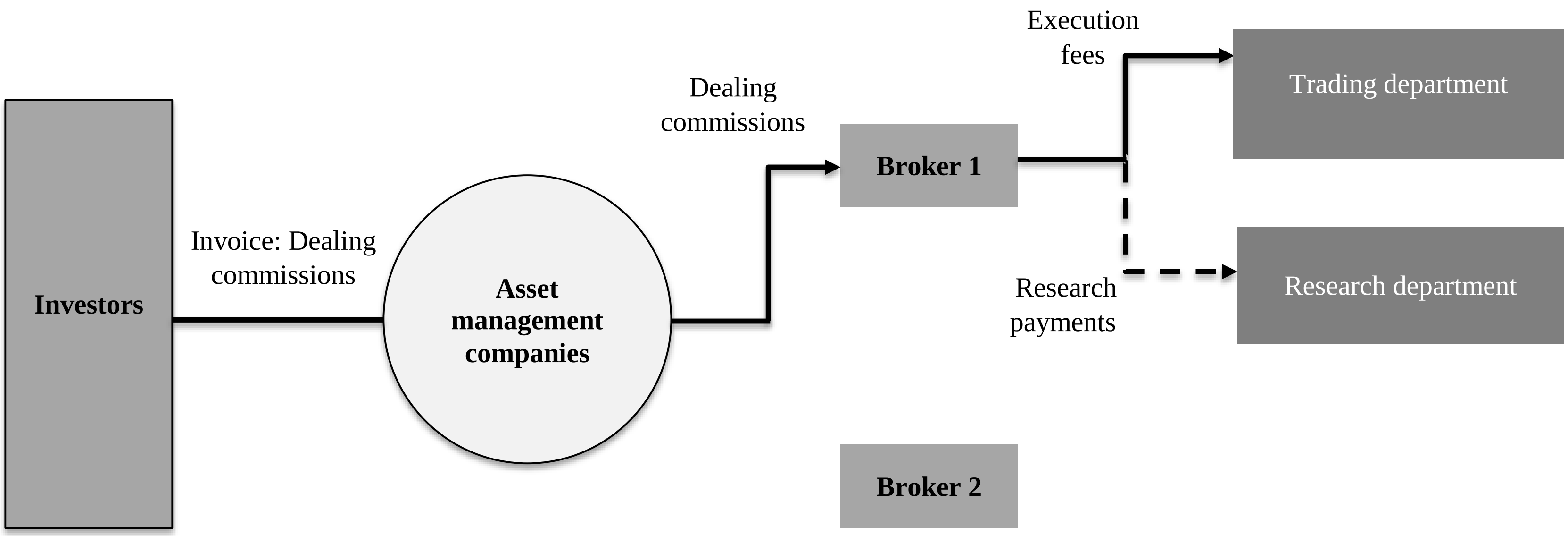
Information Brochure - Handelsbanken Fonder AB

January 12, 2016

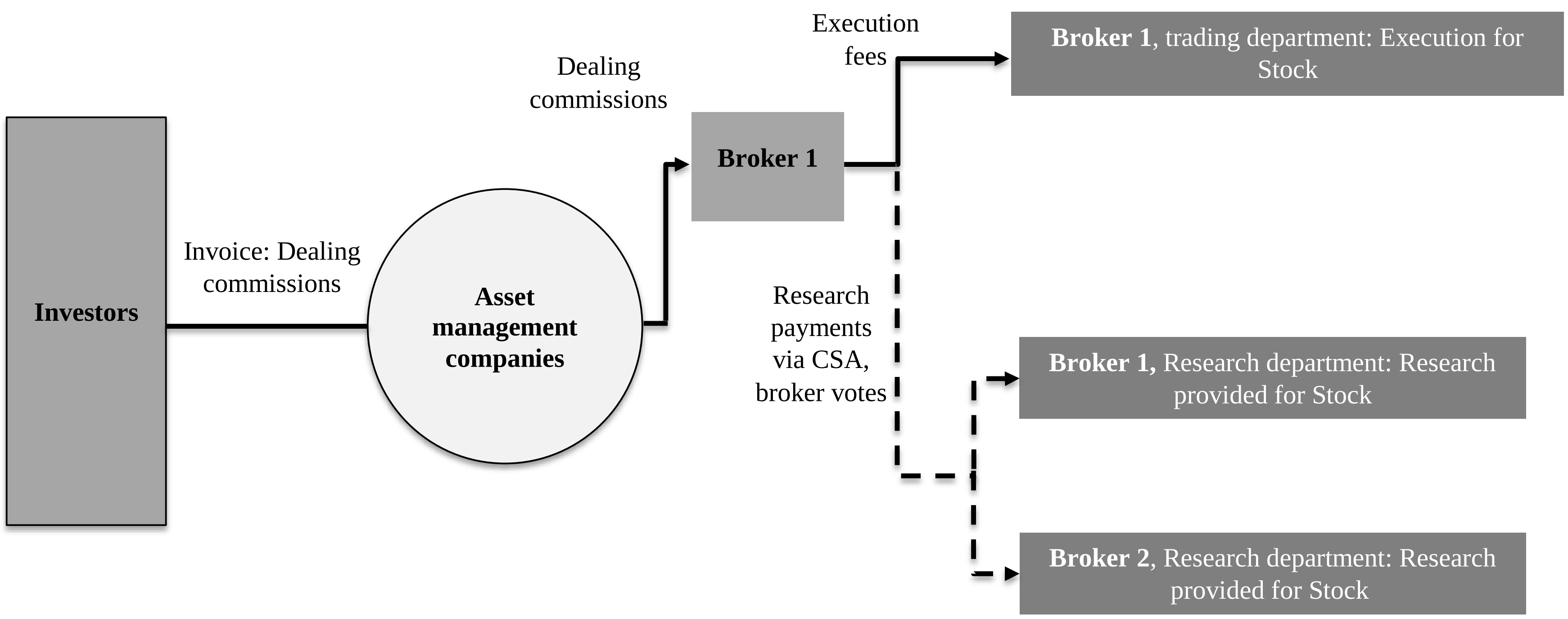
In practice, costs are deducted from each fund in the same manner as the management fee. However, the research firms invoice the Management Company on a quarterly basis, while the funds benefit daily from the purchase of the analyses. As of January 1, 2015, expenses for external analyses will be charged 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: The Bundled Model, Commission Sharing Agreement (CSA), and Research Payment Account (RPA)

Panel (A): The Bundled Model



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



Panel (C): The Unbundled Model – Research Payment Accounting (RPA)

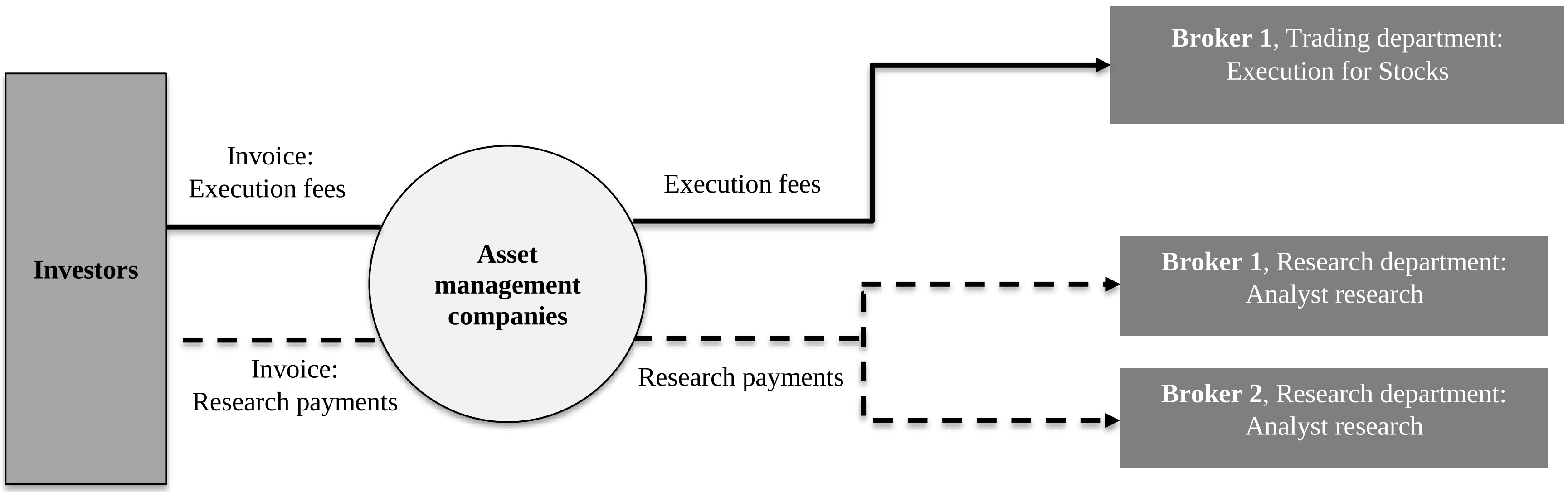


Figure 2: The identification of the treatment group and the control group

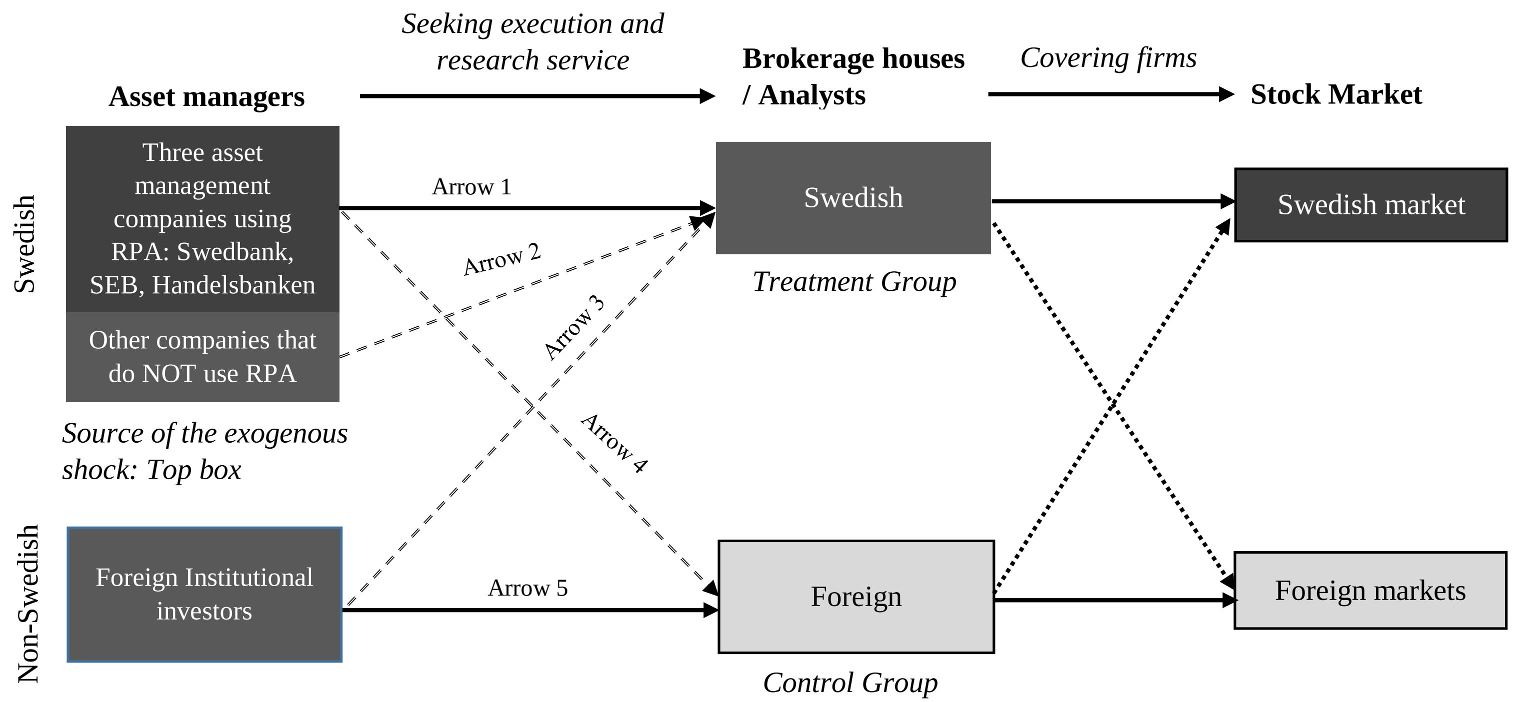


Table 1: The identification of analysts' location

This table reports the process of identifying analysts' location, the geographical distribution of identified analysts, and the treatment and the control groups construction. 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 (A): The process of identifying analysts' location

From Bloomberg	Number	Number
Equity securities listed on the Nasdaq OMX Stockholm during 2013 to 2016		379
Less preference shares and Special depositary receipts (SDR)	*46*	
Firms remained		333
Merge with I/B/E/S file		
Firms remained (tickers not found in I/B/E/S are deleted)		331
Number of analysts covering these 331 firms within 2013 to 2016		1136
Manually identifying the location of these 1136 analysts		
Number of analysts identified		1067
Number of analysts unidentified		69

Panel (B): Geographical distribution of identified analysts

Location	Number of analysts	%
UK	460	40
Sweden	267	23.22
Norway	62	5.39
France	56	4.87
US	55	4.78
Canada	52	4.52
Finland	40	3.48
Germany	29	2.52
Denmark	15	1.3
Netherlands	11	0.96
Switzerland	9	0.78
Poland	5	0.43
Russia	4	0.35
Czech Republic	2	0.17
India	2	0.17
Italy	2	0.17
South Africa	2	0.17
Spain	2	0.17
Australia	1	0.09
HK	1	0.09
Ireland	1	0.09
Malaysia	1	0.09
Portugal	1	0.09
Tunisia	1	0.09
Unidentified	69	6
Total	1,150	100
less analysts relocated internationally	14	
Distinct analysts	1,136	

Panel (C): Treatment group and control group

Treatment Group	
No. of analysts in Sweden	267
Less no. of analysts used to relocate between Sweden and other countries	*4*
No. of analysts in the treatment group	**263**
Control Group	
No. of non-Swedish analysts	**800**
No. of non-Swedish EU analysts	**688**

Table 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-year basis. The treatment (control) group has 264 Swedish (800 non-Swedish or 688 non-Swedish EU) analysts during the sample period. In this table, the dependent variable is *NUMFIRM* (or *Ln*(*NUMFIRM*)), which is defined as the number of firms followed by each individual analyst within a year (or in the natural logarithm form). *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. *Ln(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. *Ln(NUMIND)* denotes the number of two-digit SIC industries followed by each individual analyst within each year in the natural logarithm form. *Ln(PACY)* denotes the relative accuracy score in the natural logarithm form 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) 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

	Treatment: SW=1				Control: SW=0				Control: SW=0 (EU only)			
Variable	n	Mean	S.D.	Median	n	Mean	S.D.	Median	n	Mean	S.D.	Median
NUMFIRM	561	8.49	5.19	8.00	2429	13.78	7.55	12.00	2087	12.68	6.82	12.00
Ln(NUMFIRM)	561	1.89	0.80	2.08	2429	2.45	0.65	2.48	2087	2.37	0.63	2.48
RPA	561	0.50	0.50	0.00	2429	0.50	0.50	1.00	2087	0.50	0.50	1.00
Ln(GEXP)	561	2.07	0.92	2.08	2429	2.24	0.82	2.20	2087	2.23	0.83	2.20
Ln(NUMIND)	561	1.00	0.69	1.10	2429	0.95	0.67	1.10	2087	0.95	0.66	1.10
Ln(PACY)	561	3.93	0.36	3.99	2429	3.96	0.26	4.00	2087	3.96	0.27	4.00
No. of analysts	264				800				688			

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

Dep.Var.=	*NUMFIRM*			*Ln(NUMFIRM)*		
	All		EU only	All		EU only
	i	ii	iii	iv	v	vi
RPA	0.684***			0.021		
	(0.214)			(0.019)		
SW × *RPA*	-0.840***	-0.855***	-0.677**	-0.090**	-0.091**	-0.099***
	(0.306)	(0.301)	(0.303)	(0.038)	(0.038)	(0.038)
Ln(GEXP)	3.196***	1.698**	1.508**	0.280***	0.177**	0.202**
	(0.523)	(0.678)	(0.687)	(0.058)	(0.073)	(0.079)
Ln(NUMIND)	6.777***	6.802***	6.541***	0.802***	0.804***	0.812***
	(0.374)	(0.374)	(0.379)	(0.040)	(0.040)	(0.041)
Ln(PACY)	0.703***	0.675***	0.507**	0.074**	0.072**	0.060
	(0.246)	(0.243)	(0.248)	(0.034)	(0.034)	(0.037)
Observations	3222	3222	2727	3222	3222	2727
Adjusted R2	0.781	0.786	0.762	0.767	0.769	0.757
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes

Table 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). We exclude SDR firms. These firms are used to test the Hypothesis 2 – the selective reduction in firms' analyst following.

Panel (A): Countries of headquarters

Country	No. of firms	%
Sweden	307	92.19
Canada	8	2.40
Finland	6	1.80
Switzerland	4	1.20
Denmark	2	0.60
UK	2	0.60
Malta	2	0.60
Poland	1	0.30
US	1	0.30
Total	333	100

Panel (B): The industry distribution

Industry	No. of firms	%
Consumer, Non-cyclical	69	20.72
Industrial	65	19.52
Consumer, Cyclical	47	14.11
Financial	47	14.11
Communications	27	8.11
Technology	26	7.81
Basic Materials	19	5.71
Energy	8	2.40
Diversified	6	1.80
Utilities	1	0.30
Unidentified	18	5.41
Total	333	100

Table 4: Selective reduction in firms' analyst following

This table reports the descriptive statistics and results for Hypothesis 2 – after the RPA adoption, the decrease in the number of analyst following is greater among small firms, firms held by less number of institutional investors, and firms that are not included in the Nasdaq OMX Stockholm Benchmark index. The test is conducted on 333 firms that are listed on the largest Swedish stock market – Nasdaq OMX Stockholm from 2013 to 2016. The analysis is on the firm-year basis. 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 year. *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. *LOWNUMINST* is a dummy variable, set equal to one when the firm has the number of institutional investors lower than the median of all firms at the end of each previous year, and zero otherwise. We use two proxies to define small firms: *SMALLMED* and *SMALLIND*. The *SMALLMED* variable is an indicator variable, with the value of one when the firm's market value of equity is less than the median of all firms at the end of each previous year, and zero otherwise. The *SMALLIND* variable is an indicator variable, with the value of one when the firm is included in the Nasdaq OMX Stockholm Small-cap index, and zero otherwise. *NONBENCH* 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 each previous year, and zero otherwise. *Ln(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. Panel (A) presents descriptive statistics for variables used in the regression. Panels (B) and (C) 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				RPA=1			
Variable	n	Mean	S.D.	Median	n	Mean	S.D.	Median
AF_SW	531	3.36	3.44	2.00	568	3.10	3.42	2.00
SMALLMED	508	0.51	0.5	1.00	534	0.51	0.50	1.00
SMALLIND	531	0.5	0.5	1.00	568	0.40	0.49	0.00
LOWNUMINST	498	0.5	0.5	1.00	528	0.49	0.50	0.00
NONBENCH	531	0.77	0.42	1.00	568	0.76	0.43	1.00
PRE	531	0.51	0.5	1.00	568	1.00	0.00	1.00
Ln(MV)	531	7.74	2.1	7.5	568	8.21	1.95	8.17
INTA	531	0.22	0.22	0.15	568	0.24	0.24	0.18
RETVOL	531	2.32	1.48	1.86	568	2.36	1.22	2.01
MB	531	4.5	9.4	2.04	568	5.59	11.57	2.49
INST	531	46.78	25.56	47.77	568	49.58	24.82	50.92

Panel (B): Results for Small firms

	SMALL - Median Cut			SMALL - Index Cut		
	i	ii	iii	iv	v	vi
SMALLMED	-0.080	-0.052	0.029			
	(0.201)	(0.203)	(0.228)			
RPA × SMALLMED	-0.448***	-0.492***	-0.409**			
	(0.157)	(0.159)	(0.158)			
PRE × SMALLMED			-0.172			
			(0.165)			
SMALLIND				-0.175	0.150	0.205
				(0.251)	(0.249)	(0.279)
RPA × SMALLIND				-0.487***	-0.524***	-0.472***
				(0.140)	(0.149)	(0.146)
PRE × SMALLIND						-0.112
						(0.168)
Ln(MV)		0.169*	0.167*		0.194**	0.193**
		(0.100)	(0.099)		(0.097)	(0.097)
INTA		-0.805*	-0.817*		-0.853*	-0.859*
		(0.424)	(0.425)		(0.436)	(0.437)
RETVOL		-0.109**	-0.114**		-0.088*	-0.092*
		(0.047)	(0.046)		(0.049)	(0.048)
MB		-0.009*	-0.009*		-0.008*	-0.009**
		(0.005)	(0.005)		(0.004)	(0.004)
INST		0.004	0.004		0.008**	0.008**
		(0.003)	(0.003)		(0.003)	(0.003)
Observations	1051	1017	1017	1152	1077	1077
Adjusted R2	0.913	0.920	0.920	0.907	0.913	0.912
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel (C): Results for firms with few institutional investors and the non-benchmark firms

	Low number of Inst. Investors			NonBenchmark Firms		
	i	ii	iii	iv	v	vi
LOWNUMINST	-0.386	-0.521*	-0.524*			
	(0.293)	(0.296)	(0.304)			
RPA × LOWNUMINST	-0.332**	-0.390***	-0.393***			
	(0.138)	(0.143)	(0.136)			
PRE × LOWNUMINST			0.006			
			(0.167)			
NONBENCH				-0.023	0.147	0.065
				(0.298)	(0.282)	(0.325)
RPA × NONBENCH				-0.658***	-0.690***	-0.774***
				(0.186)	(0.195)	(0.194)
PRE × NONBENCH						0.171
						(0.225)
Ln(MV)		0.143	0.144		0.188*	0.189*
		(0.098)	(0.098)		(0.099)	(0.099)
INTA		-0.755*	-0.755*		-0.976**	-0.965**
		(0.404)	(0.405)		(0.437)	(0.438)
RETVOL		-0.103**	-0.103**		-0.091*	-0.090*
		(0.048)	(0.048)		(0.049)	(0.050)
MB		-0.008*	-0.008*		-0.009**	-0.009*
		(0.004)	(0.004)		(0.004)	(0.005)
INST		0.003	0.003		0.009**	0.009**
		(0.003)	(0.003)		(0.003)	(0.003)
Observations	1063	1000	1000	1152	1077	1077
Adjusted R2	0.913	0.921	0.921	0.908	0.913	0.913
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Analysts' research quality

The table reports the test for analysts' research quality. Panels (A) and (C) reports descriptive statistics for full sample and the mutual cover sample respectively. 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. *Ln(MV)* represents the market value of equity in the logarithm form. *AF* is the total number of analysts following a firm within each year. *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 year. *LOSS* is a dummy variable, and equals to one when the actual EPS is negative, and zero otherwise. *Ln(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. *Ln(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. *Ln(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. *Ln(NUMFIRM)* and *Ln(NUMIND)* are the logarithm-formed total numbers of firms and industries that one analyst covers within each year respectively. *Ln(PACY)* denotes the logarithm-formed relative accuracy score of an analyst in the previous year, which is calculated in line with Hong and Kubik (2003). Panels (B) and (D) outlines the results within the full sample and the mutual coverage sample respectively. Columns (i) to (iii) report the results with the sample that all identified analysts in the control group. Column (iv) reports the results with the sample that all the identified EU analysts in the control group. Column (v) 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 day level. Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5% and 1% level respectively.

Panel (A): Descriptive statistics for full sample

	Treatment: SW=1				Control: SW=0			
Variable	n	Mean	S.D.	Median	n	Mean	S.D.	Median
FORERR	16825	1.36	2.75	0.55	94701	1.42	3.19	0.40
RPA	16825	0.54	0.50	1.00	94701	0.54	0.50	1.00
Ln(MV)	16825	8.12	1.73	8.23	94701	8.99	1.72	9.02
AF	16825	17.22	11.46	14.00	94701	23.72	10.54	24.00
INTA	16825	27.88	21.69	26.41	94701	23.41	20.52	18.78
MB	16825	3.93	7.97	2.58	94701	3.44	6.07	2.29
RETVOL	16825	1.74	0.54	1.67	94701	1.92	0.81	1.68
LOSS	16825	0.04	0.20	0.00	94701	0.09	0.28	0.00
Ln(HOR)	16825	5.25	0.53	5.35	94701	5.21	0.57	5.33
Ln(FEXP)	16825	1.34	0.84	1.23	94701	1.31	0.80	1.27
Ln(GEXP)	16825	2.38	0.87	2.75	94701	2.36	0.77	2.36
Ln(NUMFIRM)	16825	2.35	0.51	2.40	94701	2.74	0.51	2.77
Ln(NUMIND)	16825	1.33	0.65	1.39	94701	1.11	0.67	1.10
Ln(PACY)	16825	3.96	0.32	4.00	94701	3.97	0.25	4.00

No. of Firms	2294
No. of Swedish analysts	213
No. of Non-Swedish analysts	751
No. of Non-Swedish EU analysts	658

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

	All identified analysts in control group			Only EU analysts in control group	Firm × Analyst FE
	i	ii	iii	iv	v
RPA	-0.056	-0.162***			
	(0.060)	(0.060)			
SW	0.213	0.233**			
	(0.138)	(0.117)			
SW × *RPA*	-0.509***	-0.446***	-0.321***	-0.274***	-0.344***
	(0.115)	(0.104)	(0.099)	(0.100)	(0.112)
Ln(MV)		-0.158***	-0.555***	-0.589***	-0.571***
		(0.033)	(0.124)	(0.133)	(0.146)
AF		-0.006	0.001	0.001	0.007
		(0.005)	(0.003)	(0.003)	(0.005)
INTA		-0.009***	-0.006	-0.008	-0.010
		(0.001)	(0.006)	(0.007)	(0.007)
MB		-0.011**	-0.005*	-0.008**	-0.002
		(0.005)	(0.003)	(0.003)	(0.003)
RETVOL		0.445***	0.232***	0.125	0.175**
		(0.071)	(0.079)	(0.084)	(0.089)
LOSS		3.710***	2.868***	3.167***	2.889***
		(0.275)	(0.283)	(0.303)	(0.340)
Ln(HOR)		0.388***	0.368***	0.316***	0.354***
		(0.025)	(0.022)	(0.022)	(0.024)
Ln(FEXP)		0.055	-0.012	-0.017	-0.057
		(0.034)	(0.017)	(0.019)	(0.042)
Ln(GEXP)		0.049	-0.104	-0.184	0.004
		(0.048)	(0.145)	(0.152)	(0.180)
Ln(NUMFIRM)		-0.112	0.037	0.041	0.037
		(0.068)	(0.076)	(0.076)	(0.098)
Ln(NUMIND)		0.010	-0.160*	-0.204**	-0.166
		(0.064)	(0.088)	(0.091)	(0.109)
Ln(PACY)		-0.282***	0.088	0.090	0.018
		(0.088)	(0.081)	(0.084)	(0.092)
Observations	111526	111526	111329	95837	85399
Adjusted R2	0.001	0.212	0.568	0.570	0.563
Firm FE	No	No	Yes	Yes	No
Analyst FE	No	No	Yes	Yes	No
Year FE	No	No	Yes	Yes	Yes
Firm × Analyst FE	No	No	No	No	Yes

Panel (C): Descriptive statistics for the sample of firms covered by both Swedish analysts and non-Swedish analysts

	Treatment: SW=1				Control: SW=0			
Variable	n	Mean	S.D.	Median	n	Mean	S.D.	Median
FORERR	12584	1.22	2.51	0.50	22828	1.18	2.39	0.47
RPA	12584	0.55	0.50	1.00	22828	0.53	0.50	1.00
Ln(MV)	12584	8.76	1.28	8.69	22828	9.31	1.32	9.52
AF	12584	21.28	10.37	20.00	22828	27.44	9.99	28.00
INTA	12584	26.68	21.89	22.11	22828	19.94	19.86	13.58
MB	12584	4.22	9.00	2.59	22828	3.31	6.85	2.38
RETVOL	12584	1.66	0.46	1.60	22828	1.71	0.59	1.59
LOSS	12584	0.03	0.16	0.00	22828	0.04	0.20	0.00
Ln(HOR)	12584	5.25	0.53	5.35	22828	5.23	0.55	5.33
Ln(FEXP)	12584	1.40	0.87	1.28	22828	1.30	0.80	1.23
Ln(GEXP)	12584	2.42	0.85	2.80	22828	2.28	0.80	2.27
Ln(NUMFIRM)	12584	2.31	0.50	2.40	22828	2.54	0.49	2.56
Ln(NUMIND)	12584	1.23	0.64	1.10	22828	1.06	0.66	1.10
Ln(PACY)	12584	3.95	0.31	3.99	22828	3.96	0.27	4.01

No. of Firms	180
No. of Swedish analysts	192
No. of Non-Swedish analysts	644
No. of Non-Swedish EU analysts	591

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

	All identified analysts in control group			Only EU analysts in control group	Firm × Analyst FE
	i	ii	iii	iv	v
RPA	-0.013	-0.199**			
	(0.081)	(0.081)			
SW	0.264*	0.251*			
	(0.155)	(0.132)			
SW × RPA	-0.400***	-0.374***	-0.283**	-0.283**	-0.327**
	(0.137)	(0.127)	(0.129)	(0.131)	(0.142)
Ln(MV)		-0.408***	-1.645***	-1.703***	-1.931***
		(0.046)	(0.303)	(0.312)	(0.370)
AF		0.009**	-0.009**	-0.009**	-0.004
		(0.004)	(0.003)	(0.004)	(0.005)
INTA		-0.007***	0.004	0.004	-0.005
		(0.002)	(0.011)	(0.012)	(0.013)
MB		0.016**	-0.004**	-0.005**	-0.003
		(0.007)	(0.002)	(0.002)	(0.002)
RETVOL		0.552***	-0.241	-0.271	-0.406*
		(0.126)	(0.190)	(0.196)	(0.224)
LOSS		2.718***	2.405***	2.491***	2.184***
		(0.455)	(0.433)	(0.444)	(0.505)
Ln(HOR)		0.306***	0.309***	0.308***	0.281***
		(0.036)	(0.032)	(0.032)	(0.033)
Ln(FEXP)		0.087*	-0.001	-0.002	-0.055
		(0.046)	(0.029)	(0.029)	(0.049)
Ln(GEXP)		0.003	0.042	0.007	0.102
		(0.051)	(0.213)	(0.218)	(0.278)
Ln(NUMFIRM)		0.140	0.246	0.228	0.437**
		(0.095)	(0.154)	(0.157)	(0.202)
Ln(NUMIND)		-0.233***	-0.398***	-0.395**	-0.608***
		(0.076)	(0.151)	(0.153)	(0.188)
Ln(PACY)		-0.231***	0.211*	0.214**	0.220*
		(0.081)	(0.108)	(0.109)	(0.133)
Observations	35412	35412	35379	34332	27105
Adjusted R2	0.003	0.167	0.508	0.509	0.532
Firm FE	No	No	Yes	Yes	No
Analyst FE	No	No	Yes	Yes	No
Year FE	No	No	Yes	Yes	Yes
Firm × Analyst FE	No	No	No	No	Yes

Table 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. *Ln(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. *Ln(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. *Ln(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. *Ln(NUMFIRM)* and *Ln(NUMIND)* are total numbers of firms and industries that one analyst covers within each quarter respectively. Panel (B) 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.	Median
DIS	51515	0.16	0.37	0.00
SW	51515	0.15	0.36	0.00
FORERR	51515	1.55	3.72	0.44
Ln(MV)	51515	8.82	1.73	8.82
AF	51515	23.27	11.47	23.00
INTA	51515	23.39	20.17	19.10
MB	51515	3.38	4.64	2.26
RETVOL	51515	1.71	0.71	1.50
LOSS	51515	0.08	0.28	0.00
Ln(FEXP)	51515	1.30	0.80	1.28
Ln(GEXP)	51515	2.30	0.80	2.33
Ln(NUMFIRM)	51515	15.63	7.97	14.00
Ln(NUMIND)	51515	3.80	2.37	3.00

Panel (B): Regression results

Dependent variable: Pr(*DIS*=1)			
	i	ii	iii
SW	0.030	-0.026	-0.248
	(0.225)	(0.225)	(0.277)
FORERR	0.029***	0.023**	0.010
	(0.010)	(0.011)	(0.008)
SW × *FORERR*	-0.007	-0.015	0.001
	(0.019)	(0.020)	(0.030)
Ln(MV)		-0.220***	-0.058
		(0.065)	(0.152)
AF		0.015	0.023**
		(0.009)	(0.011)
INTA		0.003	0.013
		(0.003)	(0.008)
MB		-0.025**	-0.008
		(0.010)	(0.007)
RETVOL		-0.280***	0.001
		(0.103)	(0.118)
LOSS		0.087	0.187
		(0.137)	(0.156)
Ln(FEXP)		-0.369***	-0.402***
		(0.074)	(0.083)
Ln(GEXP)		-0.099	-0.097
		(0.112)	(0.125)
Ln(NUMFIRM)		0.012	0.035**
		(0.012)	(0.014)
Ln(NUMIND)		-0.022	-0.101**
		(0.038)	(0.046)
Constant	-1.684***	1.088*	-1.209
	(0.095)	(0.629)	(2.092)
No. of Ob.	51515	51515	38621
Pseudo R2	0.002	0.032	0.152
Firm FE	No	No	Yes
Year FE	No	No	Yes

Table 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 firms listed on the Nasdaq OMX Stockholm exchange and 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. *ANA* 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. *ANASW* is the dummy variable, with the value of one if a Swedish analyst provides forecast revisions on the day or the next day ([0, +1]), and zero otherwise. *ANAFORE* is the dummy variable, with the value of one if a foreign (non-Swedish) 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. The size partition – Small-cap, Medium-cap, and Large-cap – represents firms that are included in the Nasdaq OMX Stockholm Small-cap index, Medium-cap index, and Large-cap index respectively within each year. Panel (A) presents descriptive statistics for variables used in the regression. Panel (B) reports the results for any analysts, regardless of the location of analysts. Panel (C) reports the results for both Swedish and foreign analysts in the sample that has removed the firm-day observations with both Swedish and foreign analysts' forecast revisions. 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

	All firms				**Small-cap firms**				**Medium-cap firms**				**Large-cap firms**			
Variable	n	Mean	S.D.	Median	n	Mean	S.D.	Median	n	Mean	S.D.	Median	n	Mean	S.D.	Median
ABS_ABRET	264134	1.44	1.59	0.95	110251	1.79	1.88	1.21	87095	1.40	1.42	0.99	66788	0.91	1.03	0.63
RPA	264134	0.53	0.50	1.00	110251	0.48	0.50	0.00	87095	0.58	0.49	1.00	66788	0.55	0.50	1.00
PRE	264134	0.77	0.42	1.00	110251	0.73	0.44	1.00	87095	0.81	0.39	1.00	66788	0.79	0.41	1.00
ANA	264134	0.13	0.34	0.00	110251	0.03	0.17	0.00	87095	0.12	0.32	0.00	66788	0.32	0.47	0.00
ANASW	264134	0.09	0.28	0.00	110251	0.02	0.15	0.00	87095	0.09	0.29	0.00	66788	0.18	0.39	0.00
ANAFORE	264134	0.06	0.24	0.00	110251	0.00	0.05	0.00	87095	0.02	0.15	0.00	66788	0.21	0.40	0.00
EARN	264134	0.01	0.09	0.00	110251	0.01	0.09	0.00	87095	0.01	0.09	0.00	66788	0.01	0.09	0.00
No. of firms	321				146				138				83			

Panel (B) Regression results for any analysts

Any analysts	Without pre-adoption dummy				With pre-adoption dummy			
	i	ii	iii	iv	v	vi	vii	viii
	All	Small	Medium	Large	All	Small	Medium	Large
ANA	0.26***	0.29***	0.35***	0.18***	0.26***	0.29***	0.33***	0.18***
	(0.02)	(0.05)	(0.03)	(0.02)	(0.02)	(0.07)	(0.04)	(0.02)
EARN	1.45***	1.50***	1.20***	1.62***	1.45***	1.50***	1.20***	1.62***
	(0.07)	(0.11)	(0.09)	(0.11)	(0.07)	(0.11)	(0.09)	(0.11)
RPA × *ANA*	0.08***	0.16*	0.07*	0.07***	0.08***	0.15	0.05	0.07**
	(0.02)	(0.09)	(0.04)	(0.02)	(0.03)	(0.11)	(0.05)	(0.03)
PRE × *ANA*					0.00	0.02	0.04	-0.00
					(0.03)	(0.10)	(0.05)	(0.03)
Observations	264134	110251	87095	66788	264134	110251	87095	66788
Adjusted R2	0.180	0.142	0.132	0.166	0.180	0.142	0.132	0.166
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel (C) Regression results for both Swedish and foreign (non-Swedish) analysts

Both analysts	Without pre-adoption dummy				With pre-adoption dummy			
	i	ii	iii	iv	v	vi	vii	viii
	All	Small	Medium	Large	All	Small	Medium	Large
ANASW	0.26***	0.28***	0.33***	0.15***	0.25***	0.27***	0.32***	0.15***
	(0.02)	(0.06)	(0.03)	(0.03)	(0.03)	(0.07)	(0.04)	(0.03)
ANAFORE	0.22***	0.53**	0.45***	0.14***	0.23***	0.69**	0.43***	0.15***
	(0.03)	(0.23)	(0.08)	(0.02)	(0.04)	(0.29)	(0.13)	(0.03)
EARN	1.47***	1.49***	1.20***	1.91***	1.47***	1.49***	1.20***	1.91***
	(0.07)	(0.11)	(0.09)	(0.20)	(0.07)	(0.11)	(0.09)	(0.20)
RPA × *ANASW*	0.11***	0.34***	0.11***	0.08**	0.11***	0.31**	0.09*	0.08**
	(0.03)	(0.11)	(0.04)	(0.03)	(0.03)	(0.13)	(0.06)	(0.04)
RPA × *ANAFORE*	-0.00	-0.19	-0.14	0.02	0.01	-0.02	-0.16	0.03
	(0.03)	(0.26)	(0.11)	(0.02)	(0.03)	(0.32)	(0.12)	(0.03)
PRE × *ANASW*					0.00	0.05	0.03	-0.00
					(0.04)	(0.10)	(0.06)	(0.04)
PRE × *ANAFORE*					-0.02	-0.33	0.04	-0.01
					(0.04)	(0.29)	(0.18)	(0.03)
Observations	258772	110234	86578	61960	258772	110234	86578	61960
Adjusted R2	0.181	0.143	0.131	0.167	0.181	0.143	0.131	0.167
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes