ABSTRACT

Title of dissertation: ANALYSTS UNCHAINED—EXPANDED INFORMATION PROCESSING CAPACITY AND EFFORT TRANSFER UNDER TECHNOLOGY ADOPTION

Ruyun Feng, Doctor of Philosophy, 2020

Dissertation directed by: Professor Michael Kimbrough
Department of Accounting and Information Assurance
Robert H. Smith School of Business

Analysts acquire and disseminate information to assist investors in equity valuation. Despite their expertise in equity valuation, sell-side analysts are economic agents with limited time and cognitive resources. The constraint on an analyst's information processing capacity is reflected by the previously documented negative association between an analyst's forecast accuracy for a focal firm and the total number of firms the analyst covers. While prior research focuses on analysts' attributes and portfolio firm characteristics as factors impinging on analysts' information processing capacity, I examine whether information technology—an exogenous factor—can alleviate this constraint. Using the recent exogenous shock of XBRL adoption, I find that the widespread adoption of XBRL expands analysts' information processing capacity. I document two consequences of this expanded capacity. As an analyst's information processing capacity increases, the analyst either improves the forecast accuracy for non-adopting firms in the existing portfolio or increases the size of the portfolio. This finding indicates that adoption of XBRL generates a positive externality from the adopting firms due to the transfer of analyst effort away from those firms. This study provides the first evidence that exogenous factors such as the adoption of new technology can expand analysts' information processing capacity, thereby allowing analysts to improve the overall quality of existing coverage and allowing more

firms to enjoy the benefits of analyst coverage. The paper also provides the new insight that information externalities can exist among firms that are fundamentally unrelated by identifying another channel—the effort channel—as a source of such externalities.

ANALYSTS UNCHAINED—EXPANDED INFORMATION PROCESSING CAPACITY AND EFFORT TRANSFER UNDER TECHNOLOGY ADOPTION

By

Ruyun Feng

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Advisory Committee:

Professor Michael Kimbrough, Chair
Professor Rebecca Hann
Professor Erkut Y. Ozbay
Professor Nick Seybert
Professor Musa Subasi

Dedication

Dedicated to my husband Alan He, and my parents Zhining Yu and Jinbao Feng

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Chapter 1: Introduction

As information intermediaries, analysts acquire and disseminate information to assist investors in equity valuation, thereby facilitating the overall efficiency of the capital market (Ramnath, Rock, and Shane 2008; Bradshaw 2011; Bradshaw, Ertimur, and O'Brien 2017). Despite their expertise in equity valuation, analysts are typical economic agents with limited time, energy, and resources (Driskill, Kirk, and Tucker 2019). The finiteness of these resources imposes a capacity constraint on how much information an analyst can process (Kahneman 1973). The constraint on an analyst's information processing capacity is reflected in the documented negative association between an analyst's forecast accuracy for a focal firm and the number of other firms the analyst covers (Clement 1999). The constraint limits the number of firms an analyst can follow while maintaining a threshold level of quality for all firms in the portfolio. Sell-side analysts cope with this constraint by providing in-depth research for only a small portfolio of selected firms.[1] The constraint also limits the analyst's ability to provide coverage of uniform quality across all firms in the portfolio because the effort devoted to one firm detracts from the effort the analyst can devote to other portfolio firms. For these reasons, researchers have examined the potential causes of analysts' information processing constraints by focusing on analysts' attributes and portfolio firm characteristics (Dechow and You 2012; Cohen, Lou, and Malloy 2014; Shahid and Hasan 2015; Koester, Lundholm, and Soliman 2016; Harford, Jiang, Wang, and Xie 2019; Driskill et al. 2019). However, there has been

[1] According to Groysberg, Healy, and Chapman (2008, P.25), "Analysts at buy-side firms are often responsible for covering an entire sector, such as technology. Of the 50-100 stocks in a sector that a buy-side analyst follows, the analyst writes reports on roughly 15 stocks at any given time. In contrast, a sell-side analyst usually covers only one segment of an industry, such as semiconductors or biotech. Sell- side analysts also write reports on only 10-15 stocks at a given time, but this number usually represents a much larger fraction of the total stocks that the analyst follows than it does for the buy-side analysts".

relatively little examination of possible exogenous factors that affect analysts' information processing constraints. In this paper, I examine whether the adoption of automating technology by firms in an analyst's portfolio alleviates an analyst's information processing constraints.

The 21st century has witnessed tremendous acceleration in the development and expansion of information technology (IT) applications. The advent of the technology era has spurred interest in the impact of IT on productivity. The link between the use of information and economic performance creates a theoretical possibility for IT to promote substantial productivity gains (Hayek 1945; Hubbard 2003). For example, analyst forecast performance is expected to improve when a firm adopts IT that allows analysts to acquire and process information about the firm more efficiently. In addition to this direct impact, widespread adoption of such technology can potentially expand analyst's information processing capacity—if the technology reduces the analysts' effort on the adopters. To examine this potential benefit of information technology, I exploit the recent adoption of automating technology innovation in financial reporting—eXtensible Business Reporting Language (XBRL).

XBRL is an extensible markup language that facilitates the automated exchange of large volumes of business data through structured taxonomies. This innovative disclosure technology requires that reporting firms create machine-readable tags for all quantitative disclosures in the financial statements and footnotes. Through the creation of such structured tags, XBRL allows computers to directly access the financial statement information and feed the information into valuation models without human intervention. Thus, XBRL eliminates the need for extensive and burdensome manual processing and reduces the potential for human error. The XBRL language also enables comparisons across time and firms and highlights contextual information about data items. By automating the process of information acquisition and processing, this new filing technology results in more efficient processing of relevant information by reducing the associated cost and effort.

In 2009, the Securities and Exchange Commission (SEC) implemented a mandate requiring companies to submit their SEC filings using XBRL. The change-over was implemented through a three-year phase-in period from 2009 to 2011. Prior studies have documented evidence of various benefits associated with XBRL adoption (Liu, Wang, and Yao 2014; Dong, Li, Lin, and Ni 2016; Bhattacharya, Cho, and Kim 2018). Researchers have found that XBRL adopters enjoy more analyst following, more accurate earnings forecasts, lower stock return synchronicity, and more immediate responses to 10-K filings from small institutional investors after the adoption. These studies provide evidence that XBRL improves the efficiency of information acquisition and processing for the adopters. The current study differs from others because the focus is on whether widespread adoption of XBRL leads to a relaxation of analysts' information processing constraints, which is a possible consequence of the reduction in the cost of information acquisition and processing for adopters of technology that also leads to reduced effort by the analyst.

Using a sample of 149,085 observations from 2009 to 2013, I test for an expansion of the analyst's information processing capacity as more firms in the analyst's portfolio adopt XBRL. Consistent with Clement (1999), I find a negative association between an analyst's forecast accuracy for a focal firm and the number of other firms the analyst is following. However, the strength of this negative association declines significantly as more peer firms in the analyst's portfolio adopt XBRL. The result is consistent with an expansion of analysts' information processing capacity due to the widespread adoption of XBRL. The results are robust under a variety of fixed effects specifications. To bolster this interpretation, I provide evidence on whether the decline in the strength of the negative association is attributable to the effort saved by analysts when covering XBRL adopters. If XBRL reduces the effort the adopters require from the analysts, then the decline in the negative association should be more pronounced for focal firms with peer firms that required a higher level of effort from the analysts before the adoption. Consistent with this expectation, I find that the decline in the negative association is more pronounced for focal firms that share coverage with adopters that have larger 10-K files.

I also examine whether the effect of XBRL on analysts' information processing capacity varies based on analysts' experience. Specifically, I expect the effect to decrease with both analysts' general and firm-specific experience. Analysts with more general experience are more likely to possess superior equity research abilities. These analysts can identify valuable information more quickly and incorporate such information in their research more efficiently. Therefore, there is relatively less room for performance improvement for more experienced analysts. Similarly, analysts who have followed the firm for a relatively long time may find the XBRL technology less useful because they already understand the idiosyncrasies of that firm's reporting practices. Moreover, analysts' research experience increases as they age. People tend to adopt new technology at slower speeds as they become older (Morris and Venkatesh 2000). Consistent with the prediction, I find analysts with more general and firm-specific experience realize lower expansion of their information processing capacity after portfolio firms adopted XBRL than those analysts with less experience.

In supplemental analyses, I examine the alternative possibility that the relaxation in analysts' information processing constraints under XBRL adoption is due to higher information spillover. The SEC argues that XBRL increases the comparability among firms via the application of standardized taxonomies. The increased comparability may also increase information spillover from peer firms to the focal firm, which can enhance the analyst's forecast performance on the focal firm as well. To address this alternative explanation, I examine the effect of XBRL for firms with both high and low probabilities of information spillover. Information spillover is more likely to exist among firms with related fundamentals. Therefore, I measure the probability of information spillover using both a firm's industry membership and its accounting information uniqueness. I find that the effect of XBRL on analysts' information processing capacity exists for peer firms with low information spillover probabilities (i.e., non-industry peers and peers with a high level of accounting uniqueness). The result bolsters confidence in the assertion that effort spillover is a source of the positive externalities under XBRL adoption documented in this paper.

Having established that the adoption of XBRL by portfolio firms leads to a relaxation of analysts' information processing constraints, I explore how analysts exploit their expanded information processing capacity. The information processing constraint limits an analyst's ability to provide uniform coverage across all firms in the portfolio, and the number of firms followed at a threshold level of quality. Therefore, I examine whether the XBRL-induced expansion in analysts' information processing capacity leads to an improvement in their coverage for the non-adopting firms[2] in their existing portfolios and an increase in the size of their portfolios.

Using a portfolio level analysis, I find a positive association between the estimated amount of effort an analyst saves from covering XBRL adopters and the average improvement in the analyst's forecast accuracy for non-adopting firms in the existing portfolio. This improvement represents a positive externality for non-adopting firms due to the transfer of analyst effort away from adopting firms to non-adopting firms. In addition, I find that the positive externality is more significant for non-adopting firms that are less important for the analyst's career, and therefore, are most likely to be ignored and sacrificed when analysts are under capacity constraints. Specifically, I find that smaller firms and firms with lower institutional holdings experience the most substantial improvements in forecast accuracy when their peer firms adopt XBRL.

Analysts also respond to the expanded information processing capacity by increasing their portfolio sizes. Specifically, there is a positive association between the estimated amount of effort saved to cover XBRL adopters and the change in the number of firms the analyst covers. This finding indicates that analysts can use the expanded capacity to cover more firms while maintaining the quality of coverage.

Analysts tend to choose their responses to the expanded information processing capacity based on their career incentives. Analysts who have superior forecast accuracy, and therefore, face fewer career concerns are more likely to use the expanded capacity to

[2] The non-adopting firms refer to the firms that do not adopt XBRL during year t. Eventually all public companies subject to filing requirements in the United States adopt XBRL. However, the staggered adoption rule means that only a fraction of firms adopted XBRL during each phase.

increase their portfolio sizes, while analysts who have inferior forecast accuracy in the past are more likely to use the expanded capacity to improve their forecast accuracy.

The paper makes several contributions. First, the paper provides the first evidence that exogenous factors, such as the adoption of new technology, can expand analysts' information processing capacity. This finding is important for all information workers who need to allocate their limited attention among multiple tasks. Also, this finding demonstrates a mechanism that potentially allows analysts to improve the quality of their overall coverage and allows more firms to enjoy the benefits of analyst coverage (e.g., more immediate market response to firms' news, higher liquidity, and lower cost of capital). These benefits have important capital market implications because the increasing volume and complexity of business activities and transactions have placed even higher demands on analysts while simultaneously making their role as information intermediaries in the capital markets more crucial than ever (Bradshaw et al. 2017; Driskill et al. 2019).

Second, this study sheds light on the possibility that information externalities exist among firms that are fundamentally unrelated. Prior literature focuses on information transfers among firms with common fundamentals, particularly industry peers, as the source of such externalities. This paper identifies another channel—the effort channel—as a source of such externalities. For any two firms that share the effort of the same information processor (i.e., an investor or an analyst), one firm can generate an externality over the other firms by changing the effort required from the information processor.

Third, this study provides indirect evidence that financial statements remain an important information source for sell-side analysts. There is a growing amount of evidence that analysts rely on alternative information channels such as private access to management or earnings guidance (Baginski and Hassell 1990; Green, Jame, Markov, and Subasi 2014; Brown, Call, Clement, and Sharp 2014). However, the finding that XBRL adoption expands analysts' information processing capacity provides indirect evidence of the importance of financial statements for analysts' equity research.

Finally, the finding that the benefits of XBRL are not limited to the adopters should be of interest to regulators because it adds to the growing evidence of benefits of automatic filing technology. This evidence is relevant to the SEC's deliberations about whether to extend XBRL to more corporate disclosures.

The remainder of this study proceeds as follows. Section 2 provides the theoretical framework. Section 3 presents the hypotheses development. Section 4 describes the sample. Section 5 outlines the research design and discusses the empirical results. Section 6 discusses supplemental analyses. Section 7 discusses the robustness tests. Section 8 concludes.

Chapter 2: Theoretical Framework and Hypothesis Development

2.1 Constraints on Sell-Side Analysts' Information Processing Capacity

Information acquisition and processing are critical to economic agents' decision-making processes (Gabaix, Laibson, Moloche, and Weinberg 2006). Traditional economic theory of perfect rationality assumes that economic agents fully consider all relevant information to achieve optimal outcomes that are consistent with utility maximization (Sheffrin 1996). The theory of "bounded rationality" expands upon the traditional rational choice theory by acknowledging that information acquisition and processing are costly due to individuals' cognitive limitations and time constraints. Specifically, the high cognitive costs associated with searching for, gathering and processing large amounts of information constrain individuals' ability to use this information optimally (Simon 1955, 1959, 1972; Grossman and Stiglitz 1980; Merton 1987; Bloomfield 2002; Hirshleifer and Teoh 2003; Peng and Xiong 2006; Engelberg 2008). Economic agents may cope with cognitive costs and time constraints by focusing only on subsets of available information and following heuristics (Peng and Xiong 2006; Falkinger 2008). Both alternatives can lead to suboptimal judgments or decisions.

Despite their expertise in information acquisition and processing, analysts are typical economic agents who are subject to both cognitive limitations and time constraints. Prior literature provides numerous examples of the suboptimal outcomes analysts face due to constraints of their information processing capacity. Abarbanell and Bernard (1992) find that analysts underreact to the recent earnings. Abarbanell and Bushee (1997) show that analysts fail to incorporate all information about future earnings contained in the fundamental signals into their forecast revisions. In addition, analysts do not assimilate complex information such as accruals and complex tax law changes (Bradshaw, Richardson, and Sloan 2001; Plumlee 2003).

The limitations on analysts' information processing capacity often arise because they perform multiple tasks for multiple firms.[3] Cohen et al. (2014) find that analysts who follow more firms are less likely to ask questions during firms' earnings conference calls. Driskill et al. (2019) demonstrate that an analyst is less likely to issue timely earnings forecasts for the subsequent quarter if the analyst covers more than one firm that announced earnings on the same date. When faced with multiple equity research tasks under cognitive and time constraints, the amount of effort an analyst spends on a particular firm inevitably reduces the amount of effort allocable to the other firms in a portfolio. Consequently, an analyst's forecast performance for an individual firm can be negatively affected by the effort the analyst devotes to other firms in the portfolio. Clement's (1999) finding of a negative association between an analyst's forecast accuracy for a particular firm and the number of the other firms the analyst follows provides a direct way to measure the competition among portfolio firms for analysts' limited time and attention.

Sell-side analysts cope with capacity constraints in various ways. For example, sell-side analysts often choose to focus on relatively small portfolios of stocks. In addition, they often manage the complexity of their portfolios by avoiding overly complex firms that require more effort and following firms within the same sector or industry, a strategy that allows the maximum transfer of their knowledge and expertise (Groysberg et al. 2008;

[3] Sell-side analysts provide periodic equity research reports for each firm in their portfolio. A typical report consists of (1) an analysis of the firm's financial performance, earnings growth, and equity value (including forecasts of earnings, sales and other key financial statement line items), (2) a discussion of specific risks relevant to the company and (3) an evaluation of the outlook for the business sector in which the company operates. An analyst incurs non-negligible costs to collect and analyze information about a firm in order to prepare an informative research report.

Groysberg and Healy 2013; Guan, Wong, and Zhang 2015). Analysts also tend to allocate scarce effort resources strategically based on their incentives. Dechow and You (2012) and Harford et al. (2019) document that analysts play favorites among portfolio firms, and sacrifice the quality of research for firms that have less impact on their careers. These decisions reflect the compromises and trade-offs sell-side analysts make to cope with the constraints on their information processing capacity (Choi and Gupta-Mukherjee 2017).

While prior research has focused on analysts' attributes and portfolio firm characteristics as endogenous factors to explain the negative consequences of analysts' capacity constraints (Dechow and You 2012; Cohen et al. 2014; Koester et al. 2016; Harford et al. 2019; Driskill et al. 2019), little has been done to examine whether there are exogenous factors that can alleviate the constraint. Evidence concerning this issue is important because the increasing volume and complexity of business activities and transactions have placed higher demands on analysts while making their role as information intermediaries in the capital markets more crucial than ever (Bradshaw et al. 2017).

2.2 The Potential Role of IT in Expanding Analysts' Information Processing Capacity

The link between the use of information and economic performance creates the theoretical possibility for innovations in IT to promote large gains in productivity (Hayek 1945; Hubbard 2003). The emergence and rapid development of information technology in the 21st century have ignited dramatic changes in the ways financial information is disseminated and processed (Blankespoor, Miller, and White 2014; Blankespoor, Miller, and White 2014; Miller and Skinner 2015; Brown, Stice, and White 2015; Dong et al. 2016; Dugast and Foucault 2018; Blankespoor, deHaan, and Zhu 2018). In particular, the growth of search engines and the availability of content from structured data have significantly automated the process of equity research.[4] The forecast performance of an analyst is expected to improve for firms in which IT adoption allows the analyst to acquire and process information about the firm more efficiently. In addition to this direct impact, to the extent that automation reduces the time and effort required to obtain and analyze the same amount of information (Jaskowski and Rettl 2018; Blankespoor 2019), it should also expand analysts' information processing capacity at a given level of cognitive resources. Such expansion is possible since the reduction in the cost of information acquisition and processing for some firms reduces the effort those firms require from analysts. Because all firms in an analyst's portfolio compete for the analyst's effort, lower demand for effort from one firm increases the supply of effort available for other firms. Consequently, the widespread adoption of such technology can potentially alleviate the binding information processing constraints that analysts face during equity research and allow analysts to improve the coverage of existing portfolio firms or extend coverage to new firms.

The realization of these benefits depends on several critical assumptions. First, the attaining of benefits depends on whether the new technology reduces the analyst's cost of acquiring and processing information. Prior literature identifies a critical yet often ignored link between the availability of information technology and its impact on performance—the actual usage of the technology (Devaraj and Kohli 2003). Even if an automating technology brings potential benefits of reducing the equity research cost, an analyst may not adopt such technology for various reasons. For example, analysts are information

[4] According to a report released by CRISIL, a global analytical company owned by Standard & Poor's, the current model of research production and distribution by the sell-side will be disrupted by technological advances. The sell-side research teams are likely to automate structured research tasks that are of low-value and come up with differentiated insights. The time spent on structured research tasks can then be reduced from 45% to 20%~25% through intelligent automation, which leads to about 23% reduction in costs and improved margins by 310 basis points.

specialists who obtain information from public and private sources, including firms' financial reports, and earnings guidance, as well as private access to the management (Baginski and Hassell 1990; Green et al. 2014; Brown et al. 2014). Analysts may use the technology to reduce the acquisition cost of certain information only if they use and rely on such information. In addition, most analysts are equipped with research supports (e.g., data aggregators[5]) and in-house technologies that automate the process of acquiring financial information (Nocera 2004; Bhattacharya et al. 2018). Analysts who are endowed with resources and technology are less likely to find new automating technology incrementally beneficial. The psychological resistance to new technologies may also delay or even stop analysts from using the new technology. The psychology literature has long acknowledged individuals' resistance to change, including technology innovations (Mason 2006). Psychological factors such as a lack of appreciation or tolerance, fear of uncertain results due to change, and job insecurity may all have negative impacts on analysts' adapting to technology shocks. Therefore, the introduction of the technology serves only as a "noisy" proxy for the actual usage of such technology.

Second, whether the reduced equity research cost under the automating information technology leads to relaxed information processing constraints for analysts depends on how analysts allocate the effort they save. Analysts have various ways to exploit the time and energy they save with automating technology. For example, they may decide to spend more time on leisure, which increases their pleasure without affecting their work performance. Analysts can also allocate the saved effort to accommodate new job demands. Analysts

[5] Anecdotal evidence suggests that data aggregators plan to use XBRL in order to provide more timely and accurate data items (https://www.xbrl.org/guidance/using-xbrl-a-data-aggregators-perspective/). Therefore, analysts who rely on data aggregators might benefit indirectly from XBRL in the long run.

often perform several other roles for their employers in addition to secondary market information providers. For example, analysts in the investment banks are often involved in due diligence and initial valuation for the IPO deals that their banks underwrite (Pisciotta 2019). Such involvement is very time-consuming for the analysts and often does not necessarily improve the quality of their existing equity research tasks. Even if analysts decide not to shift effort away from the portfolio firm research, they can reinvest their effort back to the firms from which the effort was saved. Analysts may expand the scope or increase the depth of the current equity research for these effort-saving firms. These expanded efforts can include visiting corporate sites (Cheng, Du, Wang, and Wang 2016), enhancing private interactions with the top executives (Soltes 2014; Brown et al. 2014), and hosting investor conferences with firm management and institutional investors (Green et al. 2014). Such reinvestment improves analysts' work performance on the focal firms but does not expand their available capacity for the other portfolio firms.

2.3 A Specific Information Technology in Financial Reporting—XBRL

To provide direct evidence of whether information technology expands analysts' information processing capacity, I exploit a particularly relevant information technology in financial reporting—XBRL. I focus on XBRL because this technology was introduced specifically to reduce the acquisition and processing cost of financial statement information, but its use does not introduce a mandatory requirement for additional disclosure (SEC 2009).[6]

The SEC expects XBRL to facilitate the use of financial statement information in several ways. First, XBRL reduces the cost associated with information acquisitions by eliminating the need for extensive and burdensome manual processing. Before the introduction of XBRL, financial statements were presented mostly in Hypertext Markup Language (i.e., HTML) format in a non-standardized manner. While the HTML-formatted documents can be read by people, these documents do not capture the meaning or function of tagged elements in ways that support the automated processing of the information content. Extracting specific information from a comprehensive HTML-based financial statement requires sophisticated coding skills and intensive manual procedures. Manual tasks like searching pages of information and cutting, pasting, and re-keying the relevant information into a single software file significantly increase the costs of using such information. XBRL solves this problem through the creation of structured tags that are machine-readable. The tags provide computers with direct access to the financial statement information, and thereby significantly reduce delays in information acquisition.

Second, XBRL reduces the information processing cost by improving the overall quality of the information. XBRL allows computers to automatically and precisely access

[6] Under the XBRL regulation, SEC mandates firms to tag or label all quantitative disclosures in the financial statements and footnotes so the amounts are machine-readable. However, the regulation does not require additional mandatory disclosure. Blankespoor (2019) does find that firms increase their detailed, quantitative disclosure in the financial statement footnotes upon implementation of XBRL detailed tagging requirements. These responses are in anticipation of reductions in market participants' information processing costs. The findings of increased disclosure, however, apply to the detailed tagging in the footnote and happen in the second year of XBRL filings, which therefore, do not align with the timeline of the current study. In addition, more disclosure usually attracts more attention from analysts and consequently takes more effort to analyze. Therefore, Blankespoor's (2019) findings should bias the current study against the documented results.

thousands of pieces of financial data that are included in financial statements and related footnotes. In the XBRL format, "Users of financial information will be able to download it directly into spreadsheets, analyze it using commercial off-the-shelf software, or use it within investment models in other software formats" (SEC 2009, P. 8). The automated process of directly obtaining and incorporating large quantities of financial statement data into various decision models eliminates the possible errors associated with human intervention. It also enables easier analyses of standardized data across time and firms, and highlight contextual information and relationships about disaggregated data items, which results in more efficient processing of such information.

Prior literature has documented various benefits associated with XBRL adoption. Researchers find that firms that adopt XBRL subsequently enjoy increased analyst following, more accurate earnings forecasts, lower stock return synchronicity, and improved responsiveness to the 10-K news from small institutional investors (Liu et al. 2014; Dong et al. 2016; Bhattacharya et al. 2018).[7] While the findings of these studies are consistent with the SEC's objectives that XBRL allows market participants to capture and analyze information more efficiently and at a lower cost (SEC 2009), they do not provide direct tests of such assumption. Instead, the improved forecast performance can be a direct outcome of firms' enriched information environment after the XBRL adoption. For example, SEC intends XBRL to increase the comparability among firms' financial statements via the application of standardized XBRL taxonomies (SEC 2009), which

[7] The evidence is consistent with analysts in general taking advantage of firms' XBRL adoption. To further address the concern that analysts do not use XBRL data in their equity research, I retrieved the comment letters submitted to SEC on both the voluntary and mandatory programs of XBRL adoption. I found comment letters submitted by individual analysts (e.g., research analysts Andrey Kuznetsov; independent analyst Pete Haynsworth), brokerage houses (e.g., Credit Suisse Group; Morgan Stanley Research), and analyst industry associations (e.g., the New York Society of Security Analysts), etc.

increases information spillover among related firms. Firms also increase their disclosure in the financial statement footnotes upon the implementation of XBRL's detailed tagging requirements in anticipation of reductions in market participants' information processing costs (Blankespore 2019). Therefore, it remains an empirical question whether analysts are able to save effort from covering XBRL adopters. In addition, analysts incur significant learning costs during the initial years of XBRL adoption. And the data quality under XBRL varies significantly across firms since the financial statements filed under XBRL are not subject to any mandatory auditing procedures (AICPA 2017). Therefore, the amount of effort required to efficiently use the technology may well exceed the effort saved.

While these studies focused on the direct benefits of XBRL to the adopters, their findings also point to the possibility that a firm's XBRL adoption may have a broader benefit of expanding analysts' information process capacity if analysts can save effort from more efficient information acquisition and processing under XBRL. Such benefit is possible because the reduction in the cost of information acquisition and processing for the XBRL adopter may also reduce the effort the adopter requires from analysts. Because all firms in an analyst's portfolio compete for the analyst's effort, lower demand for effort from one firm increases the supply of effort available for other firms. Therefore, the expanded capacity may allow analysts to improve the coverage of existing portfolio firms and/or extend the coverage to new firms.

Chapter 3: Hypothesis Development

As discussed in section 2.2, a firm's adoption of automating technology such as XBRL potentially reduces the cost of information acquisition and processing for the adopter. If this reduced cost translates into lower effort required from the analyst, then the analyst can devote more time and effort to the other firms in the portfolio. The alleviated competition represents a relaxation of the analyst's information processing constraint due to the effort saved from following XBRL adopters. To test for such relaxation, I examine whether the negative association between an analyst's forecast accuracy and portfolio size changes if more peer firms in the analyst's portfolio adopt XBRL. Specifically, I test the following hypothesis:

> **H1: The association between an analyst's forecast accuracy for a firm and the number of firms in the analyst's portfolio becomes less negative when more firms in the analyst's portfolio adopt XBRL.**

The expansion of the analyst's information processing capacity is a direct outcome of the time and effort the analyst can save in covering the adopters in the portfolio. Therefore, such expansion should be greater if the adopters required more effort from analysts before adopting XBRL.

XBRL reduces the adopters' demand for the analyst's effort by reducing the cost of information acquisition and processing. Firms with 10-Ks that require more intensive manual procedures in the HTML format demand greater effort from the analyst (Lehavy, Li, and Merkley 2011). If XBRL automates this manual process, and lowers the associated information cost to a standard level, the effort saved under the XBRL adoption should be the greatest for these "high effort" firms. Consequently, the relaxation in the analyst's information processing constraints under the XBRL adoption should be greater if the adopters required more effort from the analyst in the absence of XBRL. Therefore, I test the following hypothesis:

H2: The relaxation of the information processing constraint under the XBRL adoption is more pronounced when the adopters require higher effort from the analyst to acquire and process the 10-K information in the absence of XBRL.

Clement (1999) considers the analyst labor market as a tournament in which analysts with relatively better forecast performance survive. Therefore, analysts who stay in the profession for a longer time are those with superior equity research abilities. Because these analysts can identify and assimilate valuable information more efficiently, they have relatively less room for performance improvement. Similarly, analysts who have followed a specific firm for a longer time may find the XBRL technology less useful because they can better understand the idiosyncrasies of that firm's reporting practices. Moreover, analysts' research experience increases as they age. The psychology literature has found that people tend to adopt new technology at slower speeds as they become older (Morris and Venkatesh 2000). Therefore, I expect that the effect of XBRL on analysts' information processing capacity varies based on analysts' experience. Particularly, I expect the effect to decrease with both analysts' general and firm-specific experience. Thus, I examine the following hypothesis:

H3: The relaxation of the information processing constraints under the XBRL adoption is more pronounced for analysts with less experience.

Chapter 4: Data and Sample Selection

In 2009, the SEC implemented a mandate requiring companies to submit their SEC filings using XBRL through a three-year phase-in period from 2009 to 2011. In the first phase-in period, the SEC required large accelerated filers with a public float of at least $5 billion to file 10-K reports using the XBRL format for fiscal years ending on or after June 15, 2009. In the second phase-in period, public filers with a public float of at least $700 million were required to submit 10-K reports using XBRL-tagged data for fiscal periods ending on or after June 15, 2010. In the final phase-in period, all remaining public filers were mandated to submit XBRL-tagged 10-K reports for fiscal periods ending on or after June 15, 2011. Due to the misalignment of the fiscal year endings, a firm could have different numbers of peer firms adopting XBRL from 2009 to 2012.[8] For any particular firm followed by an analyst, the number of its peer firms that adopt XBRL during year t is exogenous to both the firm and the analyst. I refer to the fiscal year for which earnings have just been announced as year t-1, and I am interested in analyst earnings forecasts for year t. I construct a sample for this study using annual earnings forecasts issued by individual analysts from 2010 to 2013 to cover the period of mandatory XBRL adoption. I include year 2009 in the sample as the baseline year.

I obtain the data used in this study from multiple sources. I obtain both the analyst earnings forecasts and the actual earnings announcement date from Institutional Broker Estimate System (*I/B/E/S*) split-adjusted details data file, firm fundamentals from

[8] I define a firm's XBRL adoption date as the date the firm files its 10-K in XBRL for the first time. For example, consider firm i with a December 31 fiscal year end that announces its earnings in March of the following year. Its peer firm k has an April 30 fiscal year end and files the 10-K statement in July. If firm k adopts XBRL in 2011, it files the first 10-K in XBRL in the July of 2012. I measure forecast accuracy using the first annual forecast the analyst issues after the prior year's earnings announcement date. Therefore, the XBRL adoption of firm k is likely to affect analysts' forecast issued in 2012 for firm i's 2013 earnings.

COMPUSTAT, and stock price information from CRSP. I obtain institutional investors holdings from the Thomson Reuters institutional investors' 13-f filings. I manually collect the XBRL filings from EDGAR's database of Interactive Data Filings and RSS Feeds. For each XBRL filing, I collect the filing time, form type, and firm identity (CIK). The datasets of company filings and XBRL filings are merged with the other datasets via the link table provided by WRDS. I delete observations with missing analyst identification and forecasts made by analyst groups.[9] I also delete analysts who follow only one firm. I keep only the first annual forecast issued by the analyst for the firm's earnings of year t after the firm's earnings announcement of year t-1. The final sample consists of 149,085 firm-year analyst observations.

Table 1 presents the descriptive statistics of the variables of interest. The median (mean) absolute forecast error is 0.82 (2.62) percent. The median analyst in the sample covers 15 firms a year from 4 distinct SIC-2 industries. The relatively small portfolio with a certain level of industry specialization reflects analysts' strategy of coping with the constraints on their information processing capacity. During the sample period, most firms adopted XBRL in years 2010 and 2011. On average, about four peer firms adopted XBRL before the focal firms' earnings announcement date of year t-1 throughout the sample period.

Table 2 presents the correlation matrix of the variables of interest. The forecast error of an individual firm is positively associated with the number of other firms followed by the same analyst. The result is consistent with prior findings that the forecast performance of the focal firm was negatively affected by the number of peer firms

[9] Following Clement (1999), I remove analyst teams from the sample by excluding analysts who have a slash (/), an ampersand (&), the word "and", or the word "group" in their names from the sample.

(Clement 1999). Both the percentage and the actual number of peer firms in the analyst's portfolio that have adopted XBRL are negatively associated with the forecast error of the focal firm. The negative correlation provides preliminary evidence that peer firms' XBRL adoption alleviates the negative impact from the peer firms on the focal firm. *Post* is negatively associated with the forecast error, consistent with the prior literature that the XBRL adoption of the focal firm improves the analyst's forecast accuracy of the focal firm.

Chapter 5: Research Design and Empirical Results

5.1 Test of H1

H1 predicts that the adoption of XBRL by more peer firms alleviates the constraint on analysts' information processing capacity. Following the prior literature, I measure an analyst's capacity constraint using the negative association between the analyst's forecast accuracy for the focal firm and the number of other firms the analyst is following. Furthermore, I examine whether the negative association is attenuated as more peer firms in the analyst's portfolio adopt XBRL. Specifically, I estimate the following equation

$$FE_{i,j,t}=\beta_0+\beta_1 NCOS_{i,j,t}+\beta_2 NCOS_{i,j,t}*XBRL_{i,j,t}+\beta_3 XBRL_{i,j,t}+\beta_4 POST_{i,t}+\beta_5 FIRMCONTROLS_{i,t} +\beta_6 ANALYSCONTROLS_{j,t}+\varepsilon_{i,j,t} \quad (1a)$$

Where:

$FE_{i,j,t}$ is the absolute error of the first subsequent earnings forecast for firm i issued by analyst j after firm i's prior year's earnings announcement date. The forecast error is deflated by the beginning of year price of firm i.

$NCOS_{i,j,t}$ is the number of other firms followed by analyst j during year t, excluding firm i.

$XBRL_{i,j,t}$ is the percentage of firms in analyst j's portfolio (excluding firm i) that have adopted XBRL by firm i's prior year's earnings announcement date.

The dependent variable is the accuracy of the first forecast for firm i's earnings of year t, issued by analyst j after firm i's earnings announcement of year t-1. I use earnings forecast accuracy as the outcome variable for several reasons. First, earnings forecast accuracy is reflective of analysts' effort because analysts have incentives to devote effort to improve the forecast accuracy. Previous studies have shown that the earnings forecast accuracy has a significant impact on analysts' career prospects. For example, relatively accurate forecasters are more likely to receive higher compensation and avoid unfavorable career outcomes (e.g., Mikhail, Walther, and Willis 1999; Hong and Kubik 2003). Second, earnings forecast accuracy is an important metric of analysts' equity research performance that receives wide interest from researchers (O' Brien 1990; Butler and Lang 1991; Clement 1999; Mikhail et al. 1999; Kim, Lobo, and Song 2011; Hilary and Shen 2013). Analysts' earnings forecasts are useful not only as a stand-alone output but also as an input to their stock recommendations (Loh and Mian 2006; Brown et al. 2014). Third, earnings forecast accuracy can be measured directly using publicly available data.

I measure the forecast accuracy of firm i using the first annual forecast the analyst issues after the earnings announcement date for firm i's prior year earnings. I use the first forecast instead of the last forecast because analysts are less subject to time or effort constraints when issuing the last forecast. Analysts can always gradually improve their forecast by incorporating previously missed information. Prior literature also shows that analysts tend to herd towards each other at the end of the year (Trueman 1994; Clement and Tse 2005). The fact that the last forecast is least affected by the competition for analysts' limited resources makes it less likely to reflect the benefits of XBRL adoption due to effort spillover.[10] Because the dependent variable is measured in the form of absolute forecast errors, the dependent variable is inversely related to the actual forecast accuracy of the analyst (i.e., lower forecast errors indicate a higher level of forecast accuracy).

The independent variables of interest are the number of firms followed by the same analyst as firm i (*NCOS*), and the interaction term between *NCOS* and the percentage of peer firms in the analyst's portfolio that have adopted XBRL before firm i's earnings

[10] In a robustness test, I used the last earnings forecast issued by the analyst during the first 11 month of the year. The result is robust to the alternative measure.

announcement of year t-1(*NCOS*XBRL*).[11] Following prior work (e.g., Mikhail, Walther, and Willis 1997; Ali, Chen, and Radhakrishnan 2007), I control for known firm characteristics of analysts' forecast accuracy. Specifically, I control for the firm size, market to book ratio, the magnitude of the earnings, earnings variability, profitability, information complexity and asymmetry, and number of analysts that follow the firm. Firm size is measured as the natural log of the firm's total asset at the end of the year, which captures the overall information environment of the firm. Market to book ratio is the ratio of the market value of the firm's common equity divided by the book value of the firm's common equity, which captures the growth opportunity. I control for the magnitude of earnings using the absolute value of EPS, earnings variability using the standard deviation of the firm's EPS for the last 10 years, firm profitability using ROE, information complexity and asymmetry using R&D activities, and the competitive environment of analysts in providing useful forecasts by using the number of analysts following the firm. I control for changes in the focal firm's demand for an analyst's attention by controlling for whether the focal firm has adopted XBRL.

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[11] It is equivalent to construct the interaction term as the number of peer firms that have adopted XBRL before the earnings announcement date, and write model (1a) as

$$FE_{i,j,t}=\beta_0+\beta_1 NCOS_{i,j,t}+\beta_2 XBRLNCOS_{i,j,t}+\beta_3 XBRL_{i,j,t}+\beta_4 POST_{i,t}+\beta_5 FIRMCONTROLS_{i,t} +\beta_6 ANALYSCONTROLS_{j,t}+\varepsilon_{j,t} \quad (1b)$$

Where:

$XBRLNCOS_{i,j,t}$ equals to the product of $NCOS_{i,j,t}$ and $XBRL_{i,j,t}$.

I conduct my main analysis using model (1a), and I conduct subsequent analyses in the form of model (1b) for two reasons: First, replacing the interaction term $NCOS_{i,j,t} * XBRL_{i,j,t}$ with the single variable $XBRLNCOS_{i,j,t}$ allows interaction of $XBRLNCOS_{i,j,t}$ with other cross-sectional variables and avoids three-way interaction terms. Second, the coefficients in model (1b) are easier to interpret. Specifically, $\beta_1+\beta_2$ can be interpreted as the impact from the peer firms that have adopted XBRL. And β_1 can be interpreted as the average negative impact from peer portfolio firms that have not adopted XBRL.

In addition to the firm characteristics that affect analysts' forecast accuracy, I also control for analyst-specific characteristics, including the analyst's general experience, firm-specific experience, the number of industries followed by the analyst, and the number of analysts employed by the brokerage house with which the analyst is affiliated.

Panel A of Table 3 presents the results of estimating model (1a).[12] The standard errors are adjusted for heteroskedasticity and clustered at both the firm and analyst levels. Consistent with the prior results, β_1 is significantly positive. The positive coefficient captures the negative impact of the peer firms on the focal firm's forecast accuracy due to the competition for analysts' limited time and attention among the portfolio firms. Consistent with hypothesis 1, β_2 is significantly negative. The negative coefficient indicates that the impact due to such competition becomes less negative when more peer firms in the analyst's portfolio adopt XBRL. Because the percentage of peer firms that adopt XBRL is bounded between [0,1], the result indicates that the negative impact from the peer firms is reduced by about 70% (0.037/0.051) by the time all peer firms in the analysts' portfolio have all adopted XBRL.

5.2 Test of H2

While the results from testing Hypothesis 1 demonstrate the existence of reduced information processing constraints under the XBRL adoption, these results only capture the average effect from all peer firms that have adopted XBRL. Hypothesis 2 predicts that the magnitude of such relaxation is greater for firms with 10-Ks that require higher processing effort from analysts. Li (2008, P.225) points out that "the information processing cost of longer documents is presumably higher, everything else equal, longer

[12] I did not present the results of estimating model (1b) because the coefficients of both models are largely the same. The only difference is caused by the winsorization of different variables.

documents seem more deterring and more difficult to read." Therefore, I partition peer firms into "high effort" versus "low effort" groups based on the gross size of the firm's 10-K files.[13] I identify a firm as a 'high effort' task if the size of the firm's 10-K report is in the top quartile of all 10-K statements filed during the same year. Because XBRL focuses on the tagging of the financial statement items[14], I also measure the effort demand using the number of characters contained in the tables of the annual report. To capture the varying benefits of XBRL across different peer firms, I test model (2), which allows the coefficients to vary based on the number of peer firms that require high versus low effort.

$$FE_{i,j,t}=\beta_0+\beta_1 NCOS\_HE_{i,j,t}+\beta_2 NCOS\_LE_{i,j,t}+\beta_3 XBRLNCOS\_HE_{i,j,t}+\beta_4 XBRLNCOS\_LE_{i,j,t}$$
$$+\beta_5 XBRL_{i,j,t}+\beta_6 POST_{i,t}+\beta_7 FIRMCONTROLS_{i,t}+\beta_8 ANALYSCONTROLS_{i,t}+\varepsilon_{i,j,t} \quad (2)$$

Where:

$NCOS\_HE_{i,j,t}$ is the number of firms followed by analyst j during year t with 10-K reports that require higher levels of effort from the analysts.

$NCOS\_LE_{i,j,t}$ is the number of firms followed by analyst j during year t with 10-K reports that require lower level of effort from the analysts.

$XBRLNCOS\_HE_{i,j,t}$ is the number of "high effort" firms in analyst j's portfolio that have adopted XBRL by the prior year's earnings announcement date of firm i.

$XBRLNCOS\_LE_{i,j,t}$ is the number of "low effort" firms in analyst j's portfolio that have already adopted XBRL by the prior year's earnings announcement date of firm i.

[13] Following Loughran and Mcdonald (2014), I obtained the data of firms' 10-K sizes from https://sraf.nd.edu/textual-analysis/resources/#All%20SEC%20EDGAR%20Filings%20by%20Type%20and%20Year

[14] The first stage of XBRL adoption requires the filer to apply XBRL taggings for the complete financial statements and any required financial statement schedules. The "detail tagging" of the footnotes and schedules are not required until the second year.

Table 4 presents the results of estimating equation (2). The coefficient on the number of peer firms in the high effort group is significantly greater than that of the low effort group. This result indicates that the negative impact on the forecast accuracy for a focal firm is greater from peer firms that require more effort from the analyst. Consistent with hypothesis 2, I find that XBRL reduces the analyst's constraint more when peer firms have 10-Ks that are more costly to analyze. The result supports the hypothesis that there is variation in the benefits of XBRL across peer firms that require different levels of effort. In particular, the XBRL-induced benefits are concentrated in peer firms that require the highest effort from the analyst. Moreover, the magnitude of the expanded information capacity measured in column (2) of Table 4 is almost twice the size compared with that in column (1). The result indicates that the benefits of XBRL are much more significant when the workload from the table contents on the 10-K reports is higher. The result is consistent with the fact that XBRL is most intensively applied to the financial statement section of the 10-K reports.

5.3 Test of H3

Hypothesis 3 predicts that XBRL relaxes the information processing constraints more for analysts who are less experienced. Following Clement (1999), I measure analysts' general experience using the quartile ranks of the number of years for which analyst *j* supplied at least one forecast. I measure analysts' firm-specific experience using the quartile ranks of the average number of years for which analyst *j* supplies at least one forecast for the peer firms.[15] I expect more experienced analysts to realize less benefit of relaxing information processing constraints under the XBRL adoption.

[15] I focus on the firm specific experience of the peer firm instead of the focal firm because the effect I examine is generated under peer firms' XBRL adoption.

Panel A (B) of Table 5 presents the results of estimating model (1b) for subsamples with varying analyst general (firm-specific) experience. Consistent with the prediction, I find that the expansion in analysts' capacity under the XBRL adoption is greater for analysts with less experience and non-existent for analysts with the most experience. The difference between the benefits for the least and most experienced analysts is significant. Panel C of Table 5 presents multivariate regression results. Consistent with the univariate results, the multivariate results indicate that the magnitude of the benefits are more pronounced for less experienced analysts.

Chapter 6: Supplemental Analysis

6.1 Information Spillover as Alternative Explanation

I examine whether the relaxation of analysts' information processing constraints is due to higher information spillover. The adoption of XBRL may enhance the comparability among firms via the application of the standardized taxonomies. The increased comparability among firms' financial statements may increase information spillover between the focal firm and the peer firms, which enhances the analyst's forecast performance on the focal firm as well. To address this alternative explanation, I partition the peer firms into two groups based on the probability of information spillover between the focal firm and the peer firms. I measure the probability of information spillover using two alternative proxies. The first proxy is industry membership. I examine the spillover effect of XBRL separately for peer firms with the same and different SIC-2 code as the focal firm.[16] Because information spillover typically occurs among firms with related fundamentals, particularly among industry peers, the spillover among firms in different industries is more likely attributable to the effort spillover. In addition to the industry membership, I also use firms' accounting uniqueness as an alternative proxy for the likelihood of information spillover. Firms with distinctive accounting information are less likely to generate information spillover to the other firms. Following Hoitash and Hoitash (2018), I measure a firm's accounting uniqueness using the quartile rank of the number of extended tags in firms' XBRL filings. I consider firms in the top quartile as those with highly unique accounting information and examine the spillover effect of XBRL for peer firms with both high and low levels of accounting uniqueness.

[16] My results are robust to the use of SIC-3 code and NAICS code.

Table 6 presents the results of examining the alternative explanation of information spillover. Column (1) reports the results when peer firms are classified based on industry membership. The relaxation in analysts' information processing constraints is significant regardless of whether the peer firms are from the same industry as the focal firm. The fact that such relaxation exists for industry peers means that it is possible that the XBRL-induced benefits are at least partially due to information spillover. However, because the relaxation also exists from non-industry peers, the result indicates that the effort spillover is at least one of the sources of XBRL-induced benefits. Column (2) of Table 5 reports the results of such relaxation from peer firms with both high and low levels of accounting uniqueness. I find greater relaxation from XBRL adopters with unique accounting information in which information transfers are least likely. The evidence bolsters confidence that effort spillover is a significant source of XBRL-induced benefits.

6.2 How Do Analysts Exploit the Benefits under XBRL?

In this section, I examine how analysts exploit XBRL-induced benefits. The information processing constraint limits an analyst's ability to provide coverage of uniform quality across all firms in the portfolio. The constraint also limits an analysts' ability to follow more firms while maintaining a threshold level of quality for all firms in the portfolio. Therefore, analysts can respond to the expanded information processing capacity by improving their coverage for non-adopting firms in their existing portfolio.[17] They can also use the productivity gain to follow more firms. The first channel represents an effort

[17] I refer to the non-adopting firms in an analyst's existing portfolio as the firms in the current portfolio that did not adopt XBRL during year t. the analyst's exiting portfolio consists of firms that were followed by the analyst in both year t and year t-1. Both the average forecast performance of non-adopters and the number of adopters are measured using only firms in the analyst's exiting portfolio during year t. I exclude any newly covered firms during year t in this test.

spillover from the XBRL adopters to the existing portfolio firms, while the second channel indicates an effort spillover from the adopting firms to the new portfolio firms.

6.2.1 Improved Forecast Accuracy among Existing Portfolio Firms

To examine the first channel, I test whether the average forecast performance for the non-adopting firms in the current portfolio improves more when analysts save more effort from the XBRL adoption during year t using model (3). I measure the improvement in analysts' forecast performance using both the average change in the analysts' forecast accuracy for the non-adopting firms in the portfolio and the percentage of the non-adopting firms for which the forecast accuracy of year t improves as compared with that of year t-1. I measure the effort saved by an analyst under XBRL adoption during year t using the sum of the alleviated negative impact of the adopting firms in the analyst's portfolio derived from equation (1b). Because the reduced negative impact is a direct consequence of the effort saved from the XBRL adopters, this proxy should capture the possible effort transfer from the adopting firms.

$$FORECAST\ IMPROVEMENT_{j,t}=\beta_0+\beta_1 ALLEVIATION_{j,t}+\beta_2 \Delta NCOS_{j,t}+\beta_3 CONTROLS_{j,t}+\varepsilon_{j,t} \quad (3)$$

Where:

$ALLEVIATION_{j,t}$ is the total effort analyst j save from covering the adopting firms during year t.

To allow for variations in the effort saved from different adopting firms, I use latent class analysis (LCA) to group observations into homogeneous classes with respect to the alleviated negative impact of the adopting firms.[18] Latent class analysis allows for varying effort transferred to different groups of focal firms and identifies these groups. Unlike

[18] I conduct LCA using the FLEXMIX package for R maintained by Bettina Gruen, which is available at https://CRAN.R-project.org/package=flexmix

traditional models, LCA does not require pre-specifying the determinants of effort transfer. Instead, this statistical method allows the identification of homogeneous classes of observations with respect to the effort transfer. These classes are distinguished by maximizing the log-likelihood function of normally distributed residuals through iterative simultaneous determination of coefficients for each class, the number of homogeneous classes, and the observations that belong to each class (Barth, Landsman, Raval, and Wang 2019). I first estimate model 1(b) under the LCA model using the expectation maximization algorithm (Dempster, Laird, and Rubin 1977; Tanner 1996), which iterates until the intercepts and coefficients converge for the k classes (k is the number of classes that minimizes the Bayesian Information Criterion) (Barth et al. 2019; Nylund, Asparouhov, and Muthén 2007). I then obtain the coefficients on *XBRLNCOS* for different homogeneous classes from the simultaneous estimation. The coefficients capture the varying magnitude of effort transfer from the XBRL adopters on different focal firms. Because such alleviation varies across different focal firms (i.e., the alleviation measured under LCA depends on both the effort saved form the adopting firms and the characteristics of the focal firms), I estimate the effort saved from each adopting firm by using the absolute value of both the average and the maximum coefficients across different focal firms for a given XBRL adopter.

Table 7 presents the results of estimating model (3). Panel A uses the average change in the forecast accuracy for the non-adopting firms as the dependent variable. Panel B uses the percentage of the non-adopting firms for which the forecast accuracy of year t improves compared with that of year t-1. The significantly negative (positive) coefficient on *ALLEVIATION* in Panel A (B) suggests that, on average, analysts improve their forecast performance for the remaining firms in the current portfolio due to the expanded information capacity. Such improvement is consistent with an effort spillover from the current year adopting firms to the non-adopting firms in the existing portfolio.

Although on average, analysts improve their forecast accuracy for the existing portfolio firms they follow, I find the improvement to be particularly pronounced for firms that receive lower-quality forecasts when analysts are constrained by lack of time and resources. Prior researchers find that analysts allocate effort strategically based on their career incentives—i.e., analysts devote more time and effort to firms that are relatively more important for their career concerns (e.g., their compensation, reputation, and mobility). These firms are less likely to suffer from the negative consequences of analysts' limited information processing capacity. By contrast, firms with less impact on analysts' careers will be sacrificed when analysts are under information processing constraints. Therefore, I expect the relaxation in analysts' information processing constraints as well as the effort transfer to be most pronounced for firms that have less impact on analysts' career. Following Harford et al. (2019), I measure the relative importance of a firm in the analyst's portfolio using the inversed relative quartile rank of the firm's size and institutional investor holdings among all portfolio firms followed by the analyst.[19] Firms that are most important to analysts' careers are ranked 0 and firms that are least important are ranked 1. In model (4), I interact the number of peer firms that have adopted XBRL with the relative importance of the focal firm within analyst's portfolio. Therefore, $\beta_2+\beta_3$ in model (4) captures relaxation of analysts' information processing constraint for focal

[19] The ranks are normalized to be between 0 and 1. To make the coefficient easier to interpret, I use the inverse ranks, i.e., firms with smallest sizes receive largest size ranks.

firms that are least important to the analyst's career, while β_2 captures such relaxation for focal firms that are the most important to the analyst's career.

$$FE_{i,j,t}=\beta_0+\beta_1 NCOS_{i,j,t}+\beta_2 XBRLNCOS_{i,j,t}+\beta_3 XBRLNCOS_{i,j,t}*IMPORTANCE_{i,j,t}$$
$$+\beta_4 IMPORTANCE_{i,j,t}+\beta_5 XBRL_{i,j,t}+\beta_6 POST_{i,t}+\beta_7 FIRMCONTROLS_{i,t}$$
$$+\beta_8 ANALYSCONTROLS_{i,t}+\varepsilon_{i,j,t} \quad (4)$$

Where:

$IMPORTANCE_{i,j,t}$ is the relative importance of firm i in analyst j's portfolio during year t.

Panel A of Table 8 presents the result of estimating equation (4). Column (1) measures the relative importance of firm i using the inversed quartile rank of the firm's size, and column (2) uses institutional ownership. Consistent with Harford et al. (2019), the coefficient on *IMPORTANCE* is significantly positive[20], indicating that firms that are least important to the analyst receive the worst forecast outcomes. β_3 is significantly negative across both columns, consistent with the prediction that the relaxation is the greatest for firms that previously bear the most adverse consequences when analysts are under capacity constraints. In addition, β_2 is insignificant, indicating that there is no apparent benefit for firms that are the most important for analysts' career. This is likely because firms that have the most significant impact on analysts' compensation and reputation are always prioritized to receive enough attention. These firms are much less likely to bear any negative consequences even when analysts are under binding capacity constraints, and therefore, these firms will not reflect the benefits after the constraints are relieved. Panel B (C) presents the average improvement in forecast accuracy due to

[20] The relative importance is measured using the inverse ranks. Therefore, firms that are most important to the analysts are ranked the lowest.

analysts' expanded information capacity for the non-adopting firms across different size (institutional holdings) quartile in analysts' portfolio. Consistent with the results in Panel A of Table 8, firms that are relatively smaller and have lower institutional ownership enjoy more substantial effort spillover from their adopting peers.

6.2.2. Expanded Portfolio Size

Prior literature finds that the size of an analyst's compensation is positively related to the portfolio size (Groysberg, Healy, and Maber 2011). If the automating technology expands analysts' information processing capacity, it will allow the analysts to follow more firms without negatively affecting the quality of the current portfolio firms. To examine this possibility, I test whether analysts increase the number of firms they actively follow when they save more effort from the XBRL adoption during year t using model (5). Table 9 presents the result of estimating model (5). The coefficients on both measures of *ALLEVIATION* are significantly positive (p<0.01). The results indicate that analysts extend their coverage to more firms when there are more portfolio firms adopting XBRL during the current year. The fact that the automating technology allows analysts to follow more firms indicates that analysts transfer at least some effort from the XBRL adopters to the new portfolio firms.

$$\Delta NCOS_{j,t}=\beta_0+\beta_1 ALLEVIATION_{j,t}+\beta_2 NCOS_{j,t-1}+\beta_3 CONTROLS_{j,t}+\varepsilon_{j,t} \quad (5)$$

While on average, analysts exploit the benefits of XBRL through both channels, their choices of how to use the technology depend on their incentives. Table 10 presents the results of the subsample analysis for analysts with different levels of career concerns. Previous findings show that forecast accuracy is more critical for analysts with more career concerns, i.e., analysts who have inferior forecast performance face a higher risk of unfavorable career outcomes (Hong and Kubik 2003). However, forecast accuracy is a less important determinant of analysts' compensation than the size and structure of their portfolio (Groysberg et al. 2011). Therefore, analysts with more serious career concerns might use automating technology to improve their forecast accuracy, while analysts with lower career concerns might use the automating technology to expand their portfolios. To test this, I partition analysts into quartiles based on the number of firms in their portfolio that receive superior forecasts in the previous year.[21] Analysts within the top quartile rank are considered to have the lowest career concerns. Consistent with the prediction, I find that analysts who had the most reliable forecast performance in the previous year, and therefore, face the lowest levels of career concerns only use XBRL to increase the number of firms followed without improving forecast accuracy for the existing portfolio firms. Analysts who have more serious career concerns use XBRL to both improve the forecast performance and expand the portfolios. However, analysts with more significant career concerns increase their portfolio sizes significantly less than analysts with fewer career concerns.

[21] I define a forecast as a superior forecast if the absolute error of the last forecast issued by analyst j for firm i is lower than the average forecast errors for the last forecasts issued by all other analysts following firm i during the first 11 month of the year.

Chapter 7: Robustness Test

7.1 Alternative Fixed Effect Models

In the main analyses, I present the results of estimating equation (1a) with only the year fixed effect. I carefully select the model specification based on the following reasons. First, my variable of interest—the XBRL adoption of peer firms, is an exogenous variable that is not correlated with the characteristics of firm i or those of analyst j.[22] Second, the year fixed effect controls for most of the possible unobservable variables that occurs along the same timeline as XBRL (i.e., the market-wide shock) and allows for the exploration of the remaining variations in the data.

In the robustness analyses, I present the results under various alternative fixed-effect models, including firm fixed effect, firm-year fixed effect and analyst-firm fixed effect in Table 11. The inference remains unchanged across different fixed effect models. The different models allow exploration of variance from different sources. For example, the model that controls for the firm-year fixed effect exploits variation in XBRL adoption across different analysts covering the same firm in the same year. This fixed effect model allows test of whether variations in peer firms' XBRL adoption rate are associated with variations in the negative impact from peer firms among analysts who follow the same firm during the same year. While fixed effect models strengthen the model inferences by controlling for any confounding factors, it comes at the cost of significantly reduced variation (Gunasekara, Richardson, Carter, and Blakely 2014; Mummolo and Peterson

[22] The adoption variable is exogenous to both the focal firm and the analyst on two levels. First, the actions of peer firms are exogenous to the focal firm and the analyst. Second, the adoption itself is exogenous because of a regulation shock.

2018). Also, the inclusion of some fixed effects reduces or even subsumes the contribution of the control variables[23], and may also impose the risks of over-control.

7.2 Placebo Test of the XBRL Adoption

In April 2009, the SEC adopted rules that required all public companies to comply with XBRL reporting requirements for fiscal periods ending on or after June 15, 2009. The rule outlines a three-year implementation specified in phases. Although the adoption of XBRL is mandated under the SEC regulation and therefore is exogenous to the adopters, several factors influence the probability of firms' XBRL adoption during each phase. The primary factor is the firm's market float compared with the cutoff point of each filing phase ($5 billion in 2009 and $700 million in 2010). Also, a firm's fiscal period end affects the timing of XBRL adoption (Blankespoor 2019). To address the concern that the findings in this study might be endogenous to these factors, I implement a placebo test of firms' XBRL adoption. With the assumption that the determinants of firms' timing to adopt XBRL is relatively time-invariant (e.g., public float, fiscal year-end, etc.), I construct a sample with a placebo XBRL adoption that is four years earlier than the actual adoption.[24]

Table 12 presents the results of estimating equation (1a) using the placebo sample. Contrary to the findings in the main analysis, the coefficient on the interaction term using the placebo treatment is significantly positive. Because public float is the primary factor that influences the probability of the adoption, the coefficient captures the incremental negative impact from large peer firms followed by the same analysts. The result is

[23] For example, the firm-year fixed effect subsumes the effect of all control variables for firm characteristics.
[24] Therefore, my placebo sample period is 2005-2009. I construct the placebo XBRL adoption of firm i to be t-4 to make sure the placebo sample period is close to, yet does not overlap with the actual adoption period.

consistent with Harford et al. (2019) in showing that analysts allocate more effort to larger and more visible firms because the research on those firms has a larger impact on the analysts' compensation and reputation in the labor market. The result provides evidence that the findings in this paper are not driven by endogenous determinants of the XBRL adoption.

7.3 Alternative Measure of the Outcome of Effort Transfer

In the supplemental analysis, I examine the effort spillover from the adopting firms to the existing portfolio firms by testing whether the average forecast performance for the non-adopting firms improves more when analysts save more effort from the XBRL adoption during year t. I use changes in the average forecast performance for the non-adopting firms to measure the outcome of analysts' effort transfer because higher forecast accuracy indicates higher quality of analysts' work, and therefore represents more effort investment. In Table 13, I present the results using an alternative outcome measure of such effort transfer—the change in the number of different types of forecasts issued by the analysts. Analysts issue different types of forecast along with the earnings forecast (e.g., sales forecast, capital expenditure forecast, gross margin forecast). An increase in the types of forecast represents an expanded scope of equity research for the firm, which is reflective of more significant effort transfer. Consistent with previous analysis, I find that analysts issue significantly more types of forecasts for the non-adopting portfolio firms when they save more effort from XBRL adoption.[25]

[25] In table 13, I measure the number of different types of forecasts issued by the analysts on the same date as the first earnings forecast. In the untabulated analyses, I also use alternative measures such as the number of different types of forecast issued by the analyst during the entire year, as well as the number of earnings forecast of different horizons. The results are all robust.

7.4 Simultaneous Estimation

In the supplemental analysis of how analysts respond to the expanded information processing capacity, I expect changes in the analyst forecast performance to affect changes in the number of firms analysts follow and vice versa, i.e. analyst forecast performance and portfolio size are jointly-determined endogenous variables. Following Barth, Kasznik and McNichols (2002), I control for simultaneity in the changes of analyst forecast performance and portfolio size by estimating equation (3) and (5) as a simultaneous system using 2SLS. For example, to estimate *ΔPFE* under the simultaneous system, I first regress *ΔNCOS* on all the non-endogenous variables in model (5). I then estimate model (3) where the independent variable *ΔNCOS* is replaced by the predicated value of *ΔNCOS* from the first stage.

Table 14 presents the results of the simultaneous estimation. The findings are very similar to those from the single equation estimation. The evidence suggests that correcting for potential simultaneity bias does not have a dramatic effect on my inferences, which indicates that my findings are not attributable to simultaneity bias.

7.5 Other Robustness Analyses

In the untabulated analyses, I examine model (1a) using the last earnings forecast for firm i issued by analyst j during the first 11 months of year t. The result is robust to using the alternative forecast accuracy measure. Also, the result is robust to using the alternative timing measure of firms' XBRL adoption as the date of the first XBRL filings, regardless of the filing type, issued by the firm. The result is also robust if I exclude firms whose peer firms are voluntary XBRL adopters at any point in time.

Chapter 8: Conclusion

Despite their expertise in equity valuation, analysts are typical economic agents with limited time, energy, and resources. The finiteness of these resources imposes a capacity constraint on how much information an analyst can process. As a result, all firms in the analyst's portfolio compete for the analyst's effort. And an analyst's forecast performance for a firm is negatively affected by the effort the analyst must devote to the other firms in the portfolio. While prior research has focused on analysts' attributes and portfolio firm characteristics to explain the negative consequences of the competition for attention among portfolio firms, I examine whether the adoption of automating technology by firms in the analyst's portfolio reduces such negative consequences. By exploiting the mandatory adoption of XBRL, I find that automating technology in financial reporting effectively reduces the negative impact of peer firms on the focal firm's performance by relaxing the information processing constraints of the analysts. Such relaxation is particularly pronounced when the adopters require higher effort from the analysts for the acquisition and processing of the 10-K information, and for analysts who are less experienced.

In supplemental analyses, I address the alternative explanation that relaxation in analysts' information processing constraint under XBRL could be due to higher information spillover. The findings that XBRL-induced relaxation in analysts' information processing constraint exists among firms that are in different industries from the focal firm indicates that effort spillover is a source of such relaxation. Furthermore, the evidence that the XBRL-induced benefit is more significant when peer firms have unique accounting information bolsters confidence that the effort channel is an essential source of such relaxation. The expanded information processing capacity under XBRL allows analysts to improve their coverage for non-adopting firms in their existing portfolio and increase the size of their portfolios. Furthermore, analysts choose how to use the technology based on their incentives.

The paper makes a number of contributions. This study is the first to provide evidence that exogenous factors such as the adoption of new technology can expand analysts' information processing capacity and alleviate the competition for analysts' attention among portfolio firms. The findings in this paper contribute to the analyst literature by demonstrating the possibility of loosening the constraint on analysts' information processing capacity and extending the benefits of analyst coverage to more firms. This finding is important for all information workers who need to allocate their limited attention among multiple tasks. The study also sheds light on the possibility that information externalities exist among firms that are fundamentally unrelated. Different from the prior literature that focuses on information transfers among firms with common fundamentals as the source of externalities, this study identifies another channel—the effort channel—as a source of such externalities. In addition, the study provides indirect evidence that firms' financial statements remain an important information source for sell-side analysts. Since XBRL currently applies to firms' financial statements, the finding that XBRL adoption expands analysts' information processing capacity is consistent with analysts relying on financial statement information. Finally, the findings that XBRL adopters generate positive externalities to the other firms in analysts' portfolio provides evidence that the potential benefits of XBRL can be extended beyond the adopters. The result should be of interest to regulators because it adds to the growing evidence of the overall benefits of this automatic filing technology. This evidence is relevant to the SEC’s deliberations about whether to extend XBRL to more corporate disclosures.

Appendix A: Variable Definition

Variables Measured at the Firm-Analyst-Year Forecast Level

FE	FE is computed as the absolute forecast error of analyst j's first annual earnings forecast for firm i issued after the firm i's earnings announcement for year t-1. The error is calculated as the absolute value of the difference between analyst *j*'s earnings forecast for firm *i* and the actual earnings reported by firm i in year t, deflated by the stock price at the beginning of year t.
FEXP	FEXP is the number of years in which analyst j has issued at least one earnings forecast for firm i by firm i's earnings announcement date of year t.
HORIZON	HORIZON is computed as the natural log of the difference between analyst j's earnings forecast date and the earnings announcement date of firm i for year t.
IMPORTANCE	IMPORTANCE is computed as the inverse quartile ranks of firm i's market capitalization (institutional ownership) among all firms covered by analyst j during the same year, normalized between 0 and 1. The most importance firms in the analyst portfolio receive the rank of 0 and the least importance firms receive the rank of 1.
LACKEXPERIENCE	An indicator that equals to 1 if analyst j's experience is in the bottom quartile rank, and 0 otherwise. An analyst's experience is measured alternatively with the analyst's general experience and the average firm-specific experience of all the firms covered by the analyst during year t, excluding firm i.
NCOS_HE	NCOS_HE is the number of firms followed by analyst j during year t, which require high effort from the analyst. A firm is considered to require high effort if the gross size of the firm's 10-K file (or the number of characters attributable to tables on the 10-K report) is in the top quartile among all 10-k files issued during the same year.
NCOS_LE	NCOS_LE is the number of firms followed by analyst j during year t, which require relatively low effort from the analyst.
PLACEBOXBRL	PLACEBOXBRL is the number of firms followed by analyst j during year t that receive placebo XBRL adoptions prior to firm i's earnings announcement for year t-1. A firm receives the placebo XBRL treatment four years before its actual adoption of XBRL.

XBRL	XBRL is the percentage of firms in analyst j's portfolio that have adopted XBRL prior to firm i's earnings announcement for year t-1.
XBRLNCOS	XBRLNCOS is the number of firms followed by analyst j during year t that have adopted XBRL prior to firm i's earnings announcement for year t-1.
XBRLNCOS_HE	XBRLNCOS_HE is the number of XBRL adopters followed by analyst j during year t, which require high effort from the analyst.
XBRLNCOS_LE	XBRLNCOS_LE is the number of XBRL adopters followed by analyst j during year t, which require relatively low effort from the analyst.
XBRLNCOS_HINFO	XBRLNCOS_HINFO is the number of XBRL adopters followed by analyst j during year t with high probability of information spillover. The probability of information spillover is measured alternatively with industry membership and accounting uniqueness.
XBRLNCOS_LINFO	XBRLNCOS_LINFO is the number of XBRL adopters followed by analyst j during year t with low probability of information spillover.

Variables Measured at the Firm-Year Level

POST	POST is a dummy variable that equals to 1 if the focal firm has adopted XBRL by end of year t-1, 0 otherwise.
AT	AT is computed as the natural log of firm i's total asset measured at the beginning of year t.
MTB	MTB is the market to book ratio, measured as the market value of firm i's equity divided by the book value of the equity.
R&D	R&D is measured as the R&D expense of firm i divided by the total asset of firm i. R&D is set to be 0 if missing.
ROE	ROE is calculated as Firm i's net income divided by the book value of the equity.
ROESTD	ROESTD is computed as the standard deviation of firm i's ROE for the past 10 years. I require at least 5 observations to calculate the standard deviation.

EPS	EPS is measured as firm i's earnings per share, calculated as the net income divided by the total shares outstanding
FOLLOWING	FOLLOWING is the number of analysts following firm i during year t.

Variables Measured at the Analyst-Year Level

ALLEVIATION1	ALLEVIATION1 refers to the total of the alleviated negative impact from analyst j's existing portfolio firms that adopt XBRL during the current year. The alleviated negative impact from an adopting firm is calculated using the maximum coefficient on *XBRLNCOS* estimated under the LCA approach of equation 1(b) across different focal firms followed by the same analyst as the adopting firm.
ALLEVIATION2	An alternative specification of *ALLEVIATION1*. The alleviated negative impact from an adopting firm is calculated using the average of the coefficients on *XBRLNCOS* estimated under the LCA approach of equation 1(b) across different focal firms followed by the same analyst as the adopting firm.
BROKER	BROKER is calculated as the number of analysts employed by the brokerage firm analyst j is affiliated with.
GEXP	GEXP is the number of years in which the analyst has issued at least one earnings forecast.
NCOS	NCOS is the number of firms followed by analyst j during year t, excluding firm i.
NIND	NIND is calculated as the number of distinct SIC-2 Codes for all firms followed by analyst j during year t.
% FORECAST IMPROVEMENT	% FORECAST IMPROVEMENT refers to the percentage of firms in analyst j's portfolio for which the forecast accuracy of year t improves compared with that of year t-1.
ΔBROKER	ΔBROKER is measured as the change in the number of analysts employed by the brokerage firm analyst j is affiliated with during year t.
ΔNCOS	ΔNCOS is measured as the change in the number of firms followed by analyst j during year t.

$\Delta\widehat{NCOS}$	The predicted value of the change in the number of firms followed by analyst j during year t.
ΔNIND	ΔNIND is calculated as the change in the number of industries followed by analyst j during year t.
ΔPEPS	ΔPEPS is calculated as the change in the average $EPS_{i,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t.
ΔPFE	ΔPFE is calculated as the change in the average $FE_{i,j,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t. I keep the existing portfolio constant by requiring the firms to be followed by analyst j in both year t and t-1.
$\widehat{\Delta PFE}$	The predicted value of average $FE_{i,j,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t.
ΔPFOLLOWING	ΔPFOLLOWING is calculated as the change in the average $FOLLOWING_{i,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t.
ΔPHORIZON	ΔPHORIZON is calculated as the change in the average $HORIZON_{i,j,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t.
ΔPMARRET	ΔPMARRET is measured as the change in the average $PMARRET_{i,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t. $PMARRET_{i,t}$ is calculated as the absolute value of the 12 month market-adjusted buy and hold return for firm i during year t.
ΔPMTB	ΔPMTB is measured as the change in the average $MTB_{i,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t.
ΔPROESTD	ΔPROESTD is calculated as the change in the average $ROESTD_{i,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t.
ΔPR&D	ΔPR&D is measured as the change in the average $R\&D_{i,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t.

ΔPSIZE	ΔPSIZE is measured as the change in the average $AT_{i,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t.
ΔPRETSTD	ΔPRETSTD is measured as the change in the average $PRRETSTD_{i,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t. $PRRETSTD_{i,t}$ is calculated as the standard deviation of firm i's monthly return for the past 12 months.
ΔPRETSKEWNESS	ΔPRETSKEWNESS is measured as the change in the average $PRETSKEWNESS_{j,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t. $PRETSKEWNESS_{j,t}$ is calculated as the skewness of firm i's monthly return for the past 12 months.
ΔPTRADING	ΔPTRADING is calculated as the change in the average $TRADING_{j,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t. $TRADING_{j,t}$ is calculated as the trading volume of firm i for the past 12 months.
ΔPIO	ΔPIO is measured as the change in the average $IO_{j,t}$ for all the non-adopting firms in analyst j's existing portfolio during year t. $IO_{j,t}$ is calculated as the institutional ownership of firm i.

Table 1

Descriptive Statistics

Table 1 contains descriptive statistics for the variables used in my main analyses. The sample contains 149,085 observations from 2009 to 2013. All variables are measured at analyst-firm-year level. The dependent variable FE measured in %. All variables are defined in Appendix A.

Variable	N	Mean	STD	P25	P50	P75
FE	149,085	2.620	6.169	0.274	0.821	2.298
NCOS	149,085	15.510	7.273	11	15	19
XBRL	149,085	0.417	0.384	0	0.357	0.813
XBRLNCOS	149,085	6.624	7.274	0	4	11
POST	149,085	0.434	0.496	0	0	1
HORIZON	149,085	5.646	0.511	5.652	5.883	5.897
FEXP	149,085	3.716	2.411	2	3	5
GEXP	149,085	5.796	2.758	3	6	8
BROKER	149,085	55.970	45.800	19	40	88
NIND	149,085	5.196	3.729	2	4	7
AT	149,085	8.162	1.872	6.890	8.156	9.388
MTB	149,085	3.628	5.461	1.309	2.169	3.645
R&D	149,085	0.036	0.077	0	0	0.039
ROESTD	149,085	0.532	1.665	0.050	0.097	0.256
EPS	149,085	2.291	2.379	0.740	1.650	3.010
ROE	149,085	0.181	20.130	0.032	0.102	0.174
FOLLOWING	149,085	19.160	11.410	10	18	26

Table 2

Correlation

Table 2 presents the correlation matrix for the variables used in our main analyses. Pairwise Spearman (Pearson) correlations are reported above (below) the diagonal. Correlations in bold are significant at the 10% level or lower. All variables are defined in Appendix A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)FE		**0.02**	**-0.17**	**-0.15**	**-0.19**	**0.16**	**0.05**	**-0.01**	**-0.04**	**-0.03**	**-0.15**	**-0.32**	**0.01**	**0.29**	**-0.15**	**-0.32**	**-0.23**
(2)NCOS	**0.01**		**0.08**	**0.35**	**0.06**	**0.11**	**0.18**	**0.29**	**0.18**	**0.33**	**0.05**	**-0.06**	**-0.09**	**-0.07**	**0.01**	**-0.02**	**-0.03**
(3)XBRL	**-0.12**	**0.06**		**0.91**	**0.68**	**0.05**	**0.12**	**0.23**	**0.07**	**0.05**	**0.14**	**0.09**	**-0.05**	**-0.05**	**0.09**	**0.11**	**0.14**
(4)XBRLNCOS	**-0.1**	**0.47**	**0.82**		**0.66**	**0.08**	**0.17**	**0.31**	**0.12**	**0.15**	**0.13**	**0.08**	**-0.06**	**-0.05**	**0.08**	**0.1**	**0.13**
(5)POST	**-0.13**	**0.05**	**0.67**	**0.56**		**0.06**	**0.11**	**0.18**	**0.08**	**0.01**	**0.28**	**0.1**	**-0.04**	**-0.08**	**0.15**	**-0.16**	**-0.27**
(6)HORIZON	**0.08**	**0.11**	**0.04**	**0.07**	**0.04**		**0.43**	**0.25**	**0.06**	**0.04**	**-0.02**	**0.04**	**0.07**	**0.02**	**0**	**0.02**	**0.04**
(7)FEXP	**-0.01**	**0.14**	**0.15**	**0.18**	**0.14**	**0.35**		**0.63**	**0.01**	**0.09**	**0.09**	**-0.02**	**-0.01**	**-0.06**	**0.05**	**0.05**	**0.05**
(8)GEXP	**-0.03**	**0.25**	**0.22**	**0.3**	**0.18**	**0.24**	**0.64**		**-0.05**	**0.15**	**-0.01**	**0.03**	**0.05**	**-0.02**	**-0.01**	**0.03**	0
(9)BROKER	**-0.03**	**0.13**	**0.06**	**0.11**	**0.07**	**0.02**	**0.01**	**-0.05**		**0.01**	**0.15**	**0.01**	**-0.07**	**-0.04**	**0.08**	**0.07**	**0.08**
(10)NIND	**-0.03**	**0.41**	**0.04**	**0.21**	**0.01**	**0.05**	**0.08**	**0.14**	**0.01**		**-0.05**	**0.01**	**-0.11**	**-0.07**	**0.1**	**0.17**	**-0.12**
(11)AT	**-0.09**	**0.05**	**0.15**	**0.14**	**0.27**	0	**0.11**	0	**0.15**	**-0.07**		**-0.18**	**-0.27**	**-0.28**	**0.41**	**0.21**	**0.59**
(12)MTB	**-0.06**	**-0.03**	**0.05**	**0.03**	**0.05**	0	**-0.02**	**0.02**	**0.01**	**-0.01**	**-0.15**		**0.32**	**0.19**	**0.05**	**0.42**	**0.2**
(13)R&D	**0.08**	**-0.05**	**-0.08**	**-0.08**	**0.08**	**0.01**	**-0.04**	**0.02**	**-0.07**	**-0.21**	**-0.38**	**0.22**		**0.24**	**-0.16**	**-0.05**	**0.04**
(14)ROESTD	**0.12**	**-0.03**	0	**-0.01**	**0.02**	**-0.01**	**-0.04**	**0**	**-0.02**	**-0.03**	**-0.15**	**0.37**	**0.18**		**-0.18**	**-0.15**	**-0.09**
(15)EPS	**0.03**	0	**0.08**	**0.05**	**0.11**	0	**0.03**	**-0.01**	**0.06**	**0.04**	**0.35**	**0.01**	**-0.15**	**-0.04**		**0.45**	**0.29**
(16)ROE	**-0.02**	**0.01**	0	0	0	0	0	0	**0.01**	**0.01**	**0.01**	**0.02**	**-0.02**	**0.03**	0		**0.26**
(17)FOLLOWING	**-0.16**	**-0.03**	**0.14**	**0.09**	**0.27**	**0.01**	**0.05**	**0.01**	**0.05**	**-0.14**	**0.57**	**0.05**	**-0.02**	**-0.08**	**0.24**	0	

Table 3

The Relaxation of Analysts' Information Processing Constraint under XBRL

Table 3 presents the results of estimating equation 1(a). Column (1) presents the results with no fixed effect. Column (2) presents the results under year fixed effect. Standard errors are clustered at both the firm level and the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

	$FE_{i,j,t}$	
VARIABLES	**(1)**	**(2)**
$\mathbf{NCOS_{i,j,t}}$	0.053***	0.051***
	(4.482)	(4.377)
$\mathbf{NCOS_{i,j,t}*XBRL_{i,j,t}}$	-0.038***	-0.037***
	(-3.409)	(-3.280)
$\mathbf{XBRL_{i,j,t}}$	-0.667***	0.286
	(-3.166)	(1.279)
$\mathbf{POST_{i,j,t}}$	-0.180	-0.150
	(-1.365)	(-0.999)
$\mathbf{HORIZON_{i,j,t}}$	1.037***	1.016***
	(21.103)	(20.820)
$\mathbf{FEXP_{i,j,t}}$	-0.029**	-0.023
	(-2.027)	(-1.612)
$\mathbf{GEXP_{j,t}}$	-0.086***	-0.057***
	(-6.079)	(-4.210)
$\mathbf{BROKER_{j,t}}$	-0.003***	-0.003***
	(-4.215)	(-3.707)
$\mathbf{NIND_{j,t}}$	-0.089***	-0.094***
	(-5.240)	(-5.518)
$\mathbf{AT_{i,t}}$	-0.039	-0.003
	(-0.647)	(-0.047)
$\mathbf{MTB_{i,t}}$	-0.102***	-0.098***
	(-7.796)	(-7.471)
$\mathbf{R\&D_{i,t}}$	5.462***	5.126***
	(5.079)	(4.801)
$\mathbf{ROESTD_{i,t}}$	0.569***	0.569***
	(6.047)	(6.050)
$\mathbf{EPS_{i,t}}$	0.167***	0.174***
	(4.464)	(4.686)
$\mathbf{ROE_{i,t}}$	-0.005*	-0.005**
	(-1.852)	(-2.062)
$\mathbf{FOLLOWING_{i,t}}$	-0.089***	-0.085***
	(-10.456)	(-10.010)
CONSTANT	-1.548***	-1.770***
	(-3.087)	(-3.491)
Observations	149,085	149,085
YEAR FE	NO	YES
CLUSTER BY FIRM	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.077	0.096
r2_a	0.077	0.096

Table 4

XBRL-Induced Benefits and the Effort Demand of Peer Firms

Table 4 presents the results of estimating equation (2). Column (1) presents the results when the effort demand of peer firms is measured using the quartile ranks of the gross size of the firms' 10-K reports. Column(2) presents the results when the effort demand is measured using the quartile ranks of the number of characters attributable to the tables on the 10-K reports. Standard errors are clustered at both the firm level and the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

	$FE_{i,j,t}$	
VARIABLES	**(1)**	**(2)**
$NCOS\_HE_{i,i,t}$	0.059***	0.124***
	(2.653)	(4.767)
$NCOS\_LE_{i,i,t}$	0.032***	0.013
	(3.934)	(0.981)
$XBRLNCOS\_HE_{i,i,t}$	-0.060***	-0.116***
	(-2.642)	(-4.662)
$XBRLNCOS\_LE_{i,i,t}$	-0.029**	0.002
	(-2.192)	(0.181)
$XBRL_{i,i,t}$	0.335	0.099
	(1.468)	(0.451)
$POST_{i,i,t}$	-0.148	-0.094
	(-0.974)	(-0.622)
$HORIZON_{i,i,t}$	1.013***	1.029***
	(20.855)	(21.052)
$FEXP_{i,i,t}$	-0.023	-0.027*
	(-1.620)	(-1.936)
$GEXP_{i,t}$	-0.057***	-0.056***
	(-4.227)	(-4.162)
$BROKER_{j,t}$	-0.003***	-0.002***
	(-3.755)	(-3.417)
$NIND_{j,t}$	-0.098***	-0.065***
	(-5.652)	(-3.763)
$AT_{i,t}$	-0.010	-0.064
	(-0.156)	(-0.986)
$MTB_{i,t}$	-0.098***	-0.098***
	(-7.487)	(-7.467)
$R\&D_{i,t}$	5.103***	5.652***
	(4.777)	(5.284)
$ROESTD_{i,t}$	0.569***	0.573***
	(6.054)	(6.106)
$EPS_{i,t}$	0.174***	0.180***
	(4.687)	(4.826)
$ROE_{i,t}$	-0.006**	-0.005**
	(-2.067)	(-2.084)
$FOLLOWING_{i,t}$	-0.086***	-0.077***
	(-9.718)	(-8.710)
CONSTANT	-1.816***	-1.473***
	(-3.462)	(-2.837)
Observations	149,085	149,085
YEAR FE	YES	YES
CLUSTER BY FIRM	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.096	0.098
r2_a	0.096	0.098

Table 5

XBRL-Induced Benefits and Analysts' Experience

Table 5 presents the XBRL-induced benefits for analysts with different levels of experience. Panel A presents the coefficients of such benefits for analysts with varying levels of general experience. Panel B presents the benefits for analysts with varying levels of firm-specific experience. Panel C presents the results of multivariate regression analysis for the full sample. Standard errors are clustered at both the firm level and the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

Panel A: The XBRL-Induced Benefits for Analysts with Different General Experience

Quartile For Firm Specific Experience	**Coefficient on XBRLNCOS**		
	Coefficient	**tValue**	**Prob**
1	-0.094***	-2.89	<0.01
2	-0.005	-0.34	0.735
3	-0.032*	-1.74	0.083
4	-0.010	-0.93	0.351
1-4	-0.084**	-2.43	0.015

Panel B: The XBRL-Induced Benefits for Analysts with Different Firm-Specific Experience

Quartile For General Experience	**Coefficient on XBRLNCOS**		
	Coefficient	**tValue**	**Prob**
1	-0.071***	-3.08	<0.01
2	-0.011	-0.56	0.573
3	-0.015*	-1.72	0.085
4	-0.024	-1.00	0.316
1-4	-0.046***	-3.21	<0.01

Panel C: Multivariate Regression Analysis

	$FE_{i,j,t}$	
VARIABLES	**General Experience**	**Firm-Specific Experience**
$NCOS_{i,j,t}$	0.043***	0.041***
	(4.273)	(3.847)
$XBRLNCOS_{i,j,t}$	-0.020**	-0.018*
	(-1.991)	(-1.655)
$LACKEXPERIENCE_{i,j,t}$*$XBRLNCOS_{i,j,t}$	-0.074**	-0.052**
	(-2.226)	(-2.133)
$XBRL_{i,j,t}$	0.158	0.265
	(0.707)	(1.107)
$POST_{i,j,t}$	-0.181	-0.209
	(-1.183)	(-1.350)
CONTRLS	YES	YES
LACKEXPERIENCE*CONTROLS[26]	YES	YES
LACKEXPERIENCE*YAERDUMMY	YES	YES
YEAR FE	YES	YES
CLUSTER BY FIRM	YES	YES
CLUSTER BY ANALYST	YES	YES
Observations	149,085	149,085
R-squared	0.096	0.097
r2_a	0.0962	0.0965

[26] I interact the experience indicator with the control variables and the year dummy in the multi-regression analysis to reconcile with previous subsample analysis, since the coefficients on the control variables and the year dummy are allowed to vary across different subsamples.

Table 6

Alternative Channel— Information Spillover under XBRL

Table 6 presents the results of the supplementary analysis, where I test an alternative source of XBRL-induced relaxation in analysts' information processing constraint—information spillover. Column (1) presents the results when the probability of information spillover is measured with industry membership. Column (2) presents the results when the probability of information spillover is measured with accounting antiques. Standard errors are clustered at both the firm level and the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

	$FE_{i,j,t}$	
VARIABLES	**Industry Membership**	**Accounting Uniqueness**
$NCOS_{i,j,t}$	0.052***	0.049***
	(4.270)	(4.185)
$XBRLNCOS\_HINFO_{i,j,t}$	-0.044***	-0.031***
	(-2.723)	(-2.725)
$XBRLNCOS\_LINFO_{i,j,t}$	-0.035***	-0.045***
	(-2.943)	(-3.215)
$XBRL_{i,j,t}$	0.282	0.297
	(1.231)	(1.375)
$POST_{i,j,t}$	-0.148	-0.187
	(-0.986)	(-1.256)
$HORIZON_{i,j,t}$	1.018***	0.948***
	(20.699)	(20.182)
$FEXP_{i,j,t}$	-0.023	-0.020
	(-1.627)	(-1.431)
$GEXP_{i,t}$	-0.057***	-0.051***
	(-4.197)	(-3.798)
$BROKER_{i,t}$	-0.003***	-0.002***
	(-3.660)	(-3.028)
$NIND_{j,t}$	-0.099***	-0.079***
	(-5.021)	(-4.636)
$AT_{i,t}$	-0.002	-0.011
	(-0.036)	(-0.186)
$MTB_{i,t}$	-0.098***	-0.094***
	(-7.469)	(-7.363)
$R\&D_{i,t}$	5.146***	5.056***
	(4.804)	(4.924)
$ROESTD_{i,t}$	0.569***	0.552***
	(6.046)	(5.774)
$EPS_{i,t}$	0.173***	0.134***
	(4.677)	(3.986)
$ROE_{i,t}$	-0.005**	-0.005**
	(-2.061)	(-2.091)
$FOLLOWING_{i,t}$	-0.085***	-0.078***
	(-9.989)	(-9.168)
CONSTANT	-1.759***	-1.673***
	(-3.479)	(-3.286)
Observations	148,832	143,691
YEAR FE	YES	YES
CLUSTER BY FIRM	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.096	0.091
r2_a	0.096	0.091

Table 7

Effort Transfer under XBRL—Improved Forecast Accuracy

Table 7 presents the results of whether analysts use XBRL to improve the forecast accuracy of the existing portfolio firms. Panel A measures improved forecast accuracy using the average changes in the forecast accuracy for the non-adopting firms.[27] Panel B uses the percentage of these firms for which the forecast accuracy of year t improves compared with that of year t-1. I measure the effort saved by the analysts during the current year using the total of the alleviated negative impact from analyst j's existing portfolio firms that adopt XBRL during the current year. Column (1) measures the alleviated negative impact from an adopting firm using the maximum coefficient on *XBRLNCOS* estimated under the LCA approach of equation 1(b) across different focal firms followed by the same analyst as the adopting firm. Column (2) measures the alleviated negative impact using the average coefficient on *XBRLNCOS*. Standard errors are clustered at the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.[28]

Panel A: Dependent Variable=$\Delta PFE_{j,t}$

	$\Delta PFE_{j,t}$	
VARIABLES	**(1)**	**(2)**
$ALLEVIATION1_{i,t}$	-0.704***	
	(-3.824)	
$ALLEVIATION2_{i,t}$		-5.542***
		(-3.951)
$\Delta NCOS_{i,t}$	0.017	0.017
	(0.866)	(0.862)
$\Delta NIND_{i,t}$	0.025	0.024
	(0.494)	(0.468)
$\Delta BROKER_{i,t}$	0.003	0.003
	(0.437)	(0.430)
$\Delta PHORIZON_{i,t}$	0.148***	0.148***
	(7.879)	(7.929)
$\Delta PSIZE_{i,t}$	-0.051***	-0.049***
	(-3.593)	(-3.484)
$\Delta PMTB_{i,t}$	-0.001	-0.001
	(-0.208)	(-0.220)
$\Delta PR\&D_{i,t}$	6.778	6.951
	(0.997)	(1.022)
$\Delta PROESTD_{i,t}$	0.036	0.032
	(0.403)	(0.359)
$\Delta PEPS_{i,t}$	-0.410***	-0.404***
	(-9.082)	(-8.971)
$\Delta PROE_{i,t}$	-0.189***	-0.191***
	(-2.725)	(-2.763)
$\Delta PFOLLOWING_{i,t}$	-0.052*	-0.050*
	(-1.935)	(-1.884)
CONSTANT	-0.832***	-0.810***
	(-7.896)	(-7.836)
Observations	6,487	6,487
YEAR FE	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.115	0.116
r2_a	0.113	0.114

[27] I exclude any new coverage and focus on the forecast performance of the firms in the analyst's existing portfolio that do not adopt XBRL in year t (non-adopting firms) as a cleaner way to test the effort transfer among the existing portfolio firms.

[28] $\Delta FEXP_{i,t}$ and $\Delta GEXP_{i,t}$ all equals to 1 across observations. Therefore they are subsumed in the year fixed effect.

Panel B: Dependent Variable=%FORECAST IMPROVEMENT$_{j,t}$

	%FORECAST IMPROVEMENT$_{j,t}$	
VARIABLES	**(1)**	**(2)**
ALLEVIATION1$_{i,t}$	4.215***	
	(3.849)	
ALLEVIATION2$_{i,t}$		19.923***
		(2.700)
ΔNCOS$_{i,t}$	-0.164	-0.158
	(-1.393)	(-1.347)
ΔNIND$_{i,t}$	-0.652**	-0.661**
	(-1.981)	(-2.010)
ΔBROKER$_{i,t}$	0.035	0.035
	(0.937)	(0.946)
ΔPHORIZON$_{i,t}$	-2.108***	-2.121***
	(-18.695)	(-18.816)
ΔPSIZE$_{i,t}$	0.151**	0.151**
	(2.117)	(2.115)
ΔPMTB$_{i,t}$	-0.047	-0.047
	(-1.319)	(-1.327)
ΔPR&D$_{i,t}$	-19.045	-19.832
	(-0.822)	(-0.854)
ΔPROESTD$_{i,t}$	-2.819***	-2.781***
	(-3.854)	(-3.807)
ΔPEPS$_{i,t}$	2.131***	2.104***
	(7.858)	(7.714)
ΔPROE$_{i,t}$	-0.919***	-0.923***
	(-2.618)	(-2.630)
ΔPFOLLOWING$_{i,t}$	0.696***	0.693***
	(3.407)	(3.391)
CONSTANT	51.554***	51.907***
	(87.273)	(90.691)
Observations	6,487	6,487
YEAR FE	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.114	0.113
r2_a	0.112	0.111

Table 8

Firm Importance and the Improved Forecast Accuracy under XBRL

Table 8 presents the results of estimating equation (4). Column (1) and (2) present the results when the relative importance of firm i is measured with the reversed quartile rank of firm i's size and institutional holdings among all firms followed by the same analyst, respectively. Standard errors are clustered at both the firm level and the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

Panel A: The Relaxation of Analysts' Constraints for Firms with Different Relative Importance

	$FE_{i,j,t}$	
VARIABLES	**Size**	**Institutional Ownership**
$NCOS_{i,j,t}$	0.044***	0.046***
	(3.642)	(3.862)
$XBRLNCOS_{i,j,t}$	-0.001	0.004
	(-0.116)	(0.320)
$IMPORTANCE_{i,j,t}$*$XBRLNCOS_{i,j,t}$	-0.107***	-0.122***
	(-5.933)	(-6.682)
$IMPORTANCE_{i,j,t}$	5.122***	4.663***
	(14.708)	(13.582)
$XBRL_{i,j,t}$	-1.484***	-1.141***
	(-6.453)	(-5.068)
$POST_{i,j,t}$	0.240*	0.127
	(1.683)	(0.872)
$HORIZON_{i,j,t}$	1.032***	1.024***
	(21.302)	(21.162)
$FEXP_{i,j,t}$	-0.015	-0.020
	(-1.117)	(-1.463)
$GEXP_{j,t}$	-0.054***	-0.058***
	(-3.967)	(-4.257)
$BROKER_{j,t}$	-0.004***	-0.004***
	(-5.668)	(-5.190)
$NIND_{j,t}$	-0.063***	-0.071***
	(-3.849)	(-4.267)
$AT_{i,t}$	-0.304***	-0.221***
	(-4.805)	(-3.573)
$MTB_{i,t}$	-0.067***	-0.076***
	(-5.569)	(-6.349)
$R\&D_{i,t}$	6.569***	6.218***
	(6.377)	(6.017)
$ROESTD_{i,t}$	0.522***	0.530***
	(5.920)	(6.027)
$EPS_{i,t}$	0.196***	0.195***
	(5.445)	(5.260)
$ROE_{i,t}$	-0.005**	-0.005**
	(-1.985)	(-2.098)
$FOLLOWING_{i,t}$	-0.066***	-0.067***
	(-8.346)	(-8.356)
YEAR FE	YES	YES
CLUSTER BY FIRM	YES	YES
CLUSTER BY ANALYST	YES	YES
Observations	146,816	146,816
R-squared	0.118	0.115
r2_a	0.118	0.115

Panel B: The Effort Transfer to Firms with Different Relative Sizes in Analysts' Portfolio

Size Quartile	ALLEVIATION1			ALLEVIATION2		
	Coefficient	tValue	Prob	Coefficient	tValue	Prob
1	-0.937**	-2.224	0.026	-9.839***	-3.076	<0.01
2	-0.939***	-3.483	<0.01	-9.944***	-4.350	<0.01
3	-0.548**	-2.448	0.014	-7.310***	-3.490	<0.01
4	-0.051	-0.435	0.664	-0.916	-0.864	0.388
1-4	-0.886**	-2.051	0.041	-8.923***	-2.619	<0.01

Panel C: The Effort Transfer to Firms with Different Institutional Ownership in Analysts' Portfolio

Institutional Investor Holding Quartile	ALLEVIATION1			ALLEVIATION2		
	Coefficient	tValue	Prob	Coefficient	tValue	Prob
1	-0.905**	-2.234	0.016	-10.785***	-2.983	<0.01
2	-0.883***	-2.985	<0.01	-9.130***	-4.713	<0.01
3	-0.594***	-2.743	<0.01	-7.507***	-3.721	<0.01
4	-0.122	-0.897	0.370	-1.131	-0.970	0.388
1-4	-0.783*	-1.910	0.056	-9.654***	-2.882	<0.01

Table 9

Effort Transfer under XBRL—Expanded Portfolio

Table 9 presents the results that analysts use XBRL to expand their current portfolio. Column (1) and (2) measures the effort saved by the analysts using *Alleviation1* and *Allevation2* respectively. Standard errors are clustered at both the firm level and the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

	Δ**NCOS**$_{j,t}$	
VARIABLES	**(1)**	**(2)**
ALLEVIATION1$_{i,t}$	1.849***	
	(11.471)	
ALLEVIATION2$_{i,t}$		8.119***
		(7.074)
NCOS$_{i,t-1}$	-0.139***	-0.116***
	(-18.070)	(-16.686)
Δ**BROKER**$_{i,t}$	0.010**	0.010**
	(2.191)	(2.149)
Δ**NIND**$_{i,t}$	1.601***	1.624***
	(22.685)	(23.127)
Δ**PFE**$_{i,t}$	-0.003	-0.003
	(-0.402)	(-0.363)
Δ**PSIZE**$_{i,t}$	-0.017**	-0.015**
	(-2.311)	(-1.972)
Δ**PMTB**$_{i,t}$	-0.001	-0.002
	(-0.284)	(-0.378)
Δ**PROESTD**$_{i,t}$	0.132**	0.150**
	(2.053)	(2.311)
Δ**PMARRET**$_{i,t}$	-1.426*	-1.536*
	(-1.751)	(-1.875)
CONSTANT	1.512***	1.416***
	(18.847)	(17.686)
Observations	6,487	6,487
YEAR FE	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.430	0.423
r2_a	0.430	0.422

Table 10

Effort Transfer and Analysts' Career Incentives

Table 10 presents the subsample analysis of analysts' choice to exploit XBRL-induced benefits under different incentives. Panel A resents the result for improved forecast accuracy of analysts' current portfolio when the analysts face high/low career concerns. Panel B presents the result of analysts' portfolio size increase when the analysts face high/low career concerns. Standard errors are clustered at the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

Panel A: Dependent Variable=$\Delta PFE_{j,t}$

	$\Delta PFE_{i,j,t}$			
VARIABLES	**ALLEVIATION1**		**ALLEVIATION2**	
	High Career Concerns	**Low Career Concerns**	**High Career Concerns**	**Low Career Concerns**
$ALLEVIATION_{i,t}$	-0.703***	-0.051	-6.094***	-0.748
	(-3.319)	(-0.153)	(-3.756)	(-0.303)
$\Delta NCOS_{i,t}$	0.024	0.018	0.024	0.018
	(0.966)	(0.710)	(0.961)	(0.719)
$\Delta NIND_{i,t}$	0.060	-0.121	0.058	-0.120
	(0.986)	(-1.438)	(0.953)	(-1.402)
$\Delta BROKER_{i,t}$	0.007	-0.005	0.007	-0.005
	(0.887)	(-0.784)	(0.854)	(-0.727)
$\Delta PHORIZON_{i,t}$	0.088***	0.128***	0.087***	0.128***
	(3.941)	(3.410)	(3.918)	(3.461)
$\Delta PSIZE_{i,t}$	-0.083***	0.036*	-0.081***	0.035
	(-4.809)	(1.672)	(-4.716)	(1.614)
$\Delta PMTB_{i,t}$	0.001	-0.005	0.001	-0.005
	(0.118)	(-0.344)	(0.122)	(-0.339)
$\Delta PR\&D_{i,t}$	2.766	2.057***	2.742	2.003***
	(0.310)	(3.009)	(0.308)	(2.991)
$\Delta PROESTD_{i,t}$	0.010	-0.066	0.008	-0.065
	(0.093)	(-0.484)	(0.077)	(-0.479)
$\Delta PEPS_{i,t}$	-0.511***	-0.149**	-0.502***	-0.149**
	(-9.056)	(-2.342)	(-8.946)	(-2.338)
$\Delta PROE_{i,t}$	-0.201***	-0.177	-0.207***	-0.178
	(-2.602)	(-1.155)	(-2.672)	(-1.158)
$\Delta PFOLLOWING_{i,t}$	-0.075**	-0.007	-0.074**	-0.008
	(-2.160)	(-0.198)	(-2.142)	(-0.213)
CONSTANT	-1.126***	0.368**	-1.083***	0.356**
	(-9.110)	(2.000)	(-8.897)	(1.980)
Observations	4,923	1,564	4,923	1,564
YEAR FE	YES	YES	YES	YES
CLUSTER BY	YES	YES	YES	YES
One Tail T-test of The Difference in EFFORT1	P<0.05		P<0.01	

Panel B: Dependent Variable=ΔNCOS$_{j,t}$

VARIABLES	ΔNCOS$_{j,t}$ ALLEVIATION1 High Career Concerns	ALLEVIATION1 Low Career Concerns	ALLEVIATION2 High Career Concerns	ALLEVIATION2 Low Career Concerns
ALLEVIATION$_{i,t}$	1.581***	2.884***	6.548***	12.783***
	(9.207)	(7.249)	(5.375)	(5.361)
NCOS$_{i,t-1}$	-0.116***	-0.206***	-0.096***	-0.172***
	(-13.785)	(-10.636)	(-12.527)	(-9.705)
ΔBROKER$_{i,t}$	0.011**	0.006	0.011**	0.006
	(2.102)	(0.681)	(2.057)	(0.684)
ΔNIND$_{i,t}$	1.583***	1.616***	1.604***	1.645***
	(25.344)	(27.370)	(25.788)	(27.593)
ΔPFE$_{i,t}$	-0.003	-0.016	-0.003	-0.016
	(-0.291)	(-0.911)	(-0.303)	(-0.862)
ΔPSIZE$_{i,t}$	-0.006	-0.050***	-0.003	-0.047***
	(-0.680)	(-3.143)	(-0.403)	(-2.934)
ΔPMTB$_{i,t}$	-0.004	0.009	-0.004	0.010
	(-0.876)	(0.805)	(-1.006)	(0.844)
ΔPROESTD$_{i,t}$	0.126	0.167	0.143*	0.189*
	(1.598)	(1.488)	(1.794)	(1.701)
ΔPMARRET$_{i,t}$	-0.579	-3.172**	-0.668	-3.394**
	(-0.572)	(-2.182)	(-0.656)	(-2.327)
CONSTANT	1.307***	1.913***	1.219***	1.780***
	(13.880)	(12.092)	(12.954)	(11.303)
Observations	4,923	1,564	4,923	1,564
YEAR FE	YES	YES	YES	YES
CLUSTER BY	YES	YES	YES	YES
One Tail Ttest of The Difference in EFFORT1	P<0.01		P<0.01	

Table 11

Alternative Fixed Effect Models

Table 11 presents the results of estimating equation (1a) under alternative FE models. Column (1) of table 11 reports the results under firm fixed effect. Column (2) reports the results under firm-year fixed effect. Column (3) reports the results under both year and analyst-firm fixed effect. Standard errors are clustered at the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

	$FE_{i,j,t}$		
VARIABLES	**(1)**	**(2)**	**(3)**
$NCOS_{i,j,t}$	0.021**	0.011	-0.013
	(1.973)	(1.289)	(-1.063)
$NCOS_{i,j,t}$*$XBRL_{i,j,t}$	-0.032***	-0.012**	-0.020**
	(-3.215)	(-1.967)	(-1.948)
$XBRL_{i,j,t}$	-1.054***	0.200**	0.227
	(-4.616)	(2.120)	(0.939)
CONTROLS	YES	YES	YES
YEAR FE	N	N	Y
FIRM FE	Y	N	N
FIRM-YEAR FE[29]	N	Y	N
ANALYST-FIRM FE	N	N	Y
CLUSTER BY FIRM	Y	Y	Y
CLUSTER BY ANALYST	Y	Y	Y
R-squared	0.455	0.863	0.552
r2_a	0.443	0.850	0.360

[29] I do not present the results with the firm and year fixed effect because Clement (1998) finds that controlling for firm-year effects increases the likelihood of identifying systematic deference in analysts' forecast accuracy relative to a model that controls for firm fixed effect and year fixed effect. However, my result is robust to controlling for firm and year fixed effect.

Table 12

Placebo Adoption Analysis

Table 12 presents the results of estimating equation (1a) using placebo sample. Column (1) presents the results with no fixed effect. Column (2) presents the results under year fixed effect. Standard errors are clustered at the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

	$FE_{i,j,t}$	
VARIABLES	**(1)**	**(2)**
$NCOS_{i,j,t}$	-0.010	-0.001
	(-1.268)	(-0.150)
$NCOS_{i,j,t}*PLACEBOXBRL_{i,j,t}$	0.086***	0.056***
	(4.423)	(3.084)
$PLACEBOXBRL_{i,j,t}$	1.982***	-0.765**
	(6.222)	(-2.205)
$POST_{i,j,t}$	-0.499**	-1.381***
	(-2.516)	(-5.968)
$HORIZON_{i,j,t}$	1.053***	1.034***
	(17.516)	(17.639)
$FEXP_{i,j,t}$	-0.063	-0.124***
	(-1.606)	(-3.209)
$GEXP_{j,t}$	0.039	-0.062
	(0.970)	(-1.602)
$BROKER_{j,t}$	-0.004***	-0.002**
	(-5.399)	(-2.382)
$NIND_{j,t}$	-0.129***	-0.110***
	(-5.506)	(-4.963)
$AT_{i,t}$	-0.013	-0.084
	(-0.148)	(-0.966)
$MTB_{i,t}$	-0.166***	-0.149***
	(-7.480)	(-6.683)
$R\&D_{i,t}$	5.666***	5.425***
	(4.566)	(4.351)
$ROESTD_{i,t}$	0.908***	0.889***
	(5.013)	(4.938)
$EPS_{i,t}$	0.588***	0.617***
	(7.599)	(8.034)
$ROE_{i,t}$	-0.003*	-0.004*
	(-1.673)	(-1.902)
$FOLLOWING_{i,t}$	-0.116***	-0.112***
	(-8.540)	(-8.507)
CONSTANT	-2.914***	-2.006***
	(-3.972)	(-2.852)
Observations	107,128	107,128
YEAR FE	NO	YES
CLUSTER BY FIRM	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.117	0.133
r2_a	0.116	0.133

Table 13

An Alternative Measure of the Outcome of Analysts' Effort Transfer

Table 13 presents the results of using an alternative measure as the outcome of analysts' effort transfer. Standard errors are clustered at the analyst level. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

	ΔPFORECASTTYPE$_{j,t}$	
VARIABLES	**(1)**	**(2)**
ALLEVIATION1$_{i,t}$	0.304***	
	(3.703)	
ALLEVIATION2$_{i,t}$		1.242**
		(2.380)
ΔNCOS$_{i,t}$	-0.020**	-0.020**
	(-2.008)	(-1.970)
ΔPTIME$_{i,t}$	0.103***	0.104***
	(11.165)	(11.275)
ΔNIND$_{i,t}$	0.010	0.010
	(0.387)	(0.362)
ΔBROKER$_{i,t}$	-0.008**	-0.008**
	(-2.110)	(-2.114)
ΔPSIZE$_{i,t}$	0.006	0.005
	(1.012)	(0.967)
ΔPMTB$_{i,t}$	-0.001	-0.001
	(-0.486)	(-0.486)
ΔPROE$_{i,t}$	0.001	0.000
	(0.053)	(0.005)
ΔPROESTD$_{i,t}$	-0.011	-0.009
	(-0.255)	(-0.207)
ΔPRETSTD$_{i,t}$	1.464**	1.436**
	(2.067)	(2.023)
ΔPRETSKEWNESS$_{i,t}$	0.011	0.015
	(0.191)	(0.262)
ΔPTRADING$_{i,t}$	-0.000	0.000
	(-0.022)	(0.048)
ΔPIO$_{i,t}$	0.055	0.051
	(0.583)	(0.543)
CONSTANT	0.204***	0.236***
	(4.046)	(4.761)
Observations	6,487	6,487
YEAR FE	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.035	0.034
r2_a	0.033	0.032

Table 14

Simultaneous Estimation

Table 14 presents the estimating model (3) and model (5) under a simultaneous system. All variables are defined in Appendix A. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Continuous variables are winsorized at the top and bottom 1%.

Panel A: Dependent Variable=$\Delta PFE_{j,t}$

	$\Delta PFE_{j,t}$	
VARIABLES	**(1)**	**(2)**
$ALLEVIATION1_{j,t}$	-0.805***	
	(-4.440)	
$ALLEVIATION2_{j,t}$		-6.291***
		(-4.550)
$\Delta \widehat{NCOS}_{i,t}$	0.047	0.057
	(0.376)	(0.466)
$\Delta NIND_{j,t}$	-0.092	-0.111
	(-0.721)	(-0.822)
$\Delta BROKER_{j,t}$	-0.001	-0.001
	(-0.093)	(-0.099)
$\Delta PHORIZON_{j,t}$	0.147***	0.147***
	(7.938)	(7.931)
$\Delta PSIZE_{j,t}$	-0.084***	-0.081***
	(-3.391)	(-3.250)
$\Delta PMTB_{j,t}$	-0.002	-0.002
	(-0.232)	(-0.243)
$\Delta PR\&D_{j,t}$	-9.254	-9.413
	(-1.307)	(-1.328)
$\Delta PROESTD_{j,t}$	0.033	0.028
	(0.393)	(0.331)
$\Delta PEPS_{j,t}$	-0.408***	-0.402***
	(-9.359)	(-9.261)
$\Delta PROE_{j,t}$	-0.187***	-0.190***
	(-2.657)	(-2.705)
$\Delta PFOLLOWING_{j,t}$	-0.046*	-0.045*
	(-1.745)	(-1.691)
CONSTANT	-1.061***	-1.029***
	(-6.493)	(-6.327)
Observations	6,487	6,487
YEAR FE	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.114	0.116
r2_a	0.112	0.114

Panel B: Dependent Variable= $\Delta NCOS_{j,t}$

	$\Delta NCOS_{j,t}$	
VARIABLES	**(1)**	**(2)**
$ALLEVIATION1_{i,t}$	2.045***	
	(12.448)	
$ALLEVIATION2_{i,t}$		9.538***
		(8.083)
$NCOS_{i,t-1}$	-0.138***	-0.115***
	(-17.964)	(-16.650)
$\Delta BROKER_{i,t}$	0.011**	0.010**
	(2.264)	(2.222)
$\Delta NIND_{i,t}$	1.595***	1.618***
	(25.636)	(24.120)
$\widehat{\Delta PFE}_{i,t}$	0.240***	0.252***
	(5.119)	(5.278)
$\Delta PSIZE_{i,t}$	-0.032**	-0.027*
	(-2.006)	(-1.692)
$\Delta PMTB_{i,t}$	0.001	0.001
	(0.314)	(0.257)
$\Delta PROESTD_{i,t}$	0.117*	0.135**
	(1.788)	(2.046)
$\Delta PMARRET_{i,t}$	-1.837**	-1.963**
	(-2.260)	(-2.402)
CONSTANT	1.512***	1.416***
	(18.847)	(17.686)
Observations	6,487	6,487
YEAR FE	YES	YES
CLUSTER BY ANALYST	YES	YES
R-squared	0.430	0.423
r2_a	0.430	0.422

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