Essays on Sell-Side Financial Analysts

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Abstract

Sell-side financial analysts play a crucial role as information intermediaries. On the one hand, by collecting, evaluating and disseminating value-relevant information, the analyst can influence the external information environment. On the other hand, the forecast performance of the analyst is affected by other important factors. This thesis focuses on the interaction between the central bank, the analyst and the external information environment. It includes three self-contained studies. Chapters 2 and 3 of this thesis explore the interplay between central bank monetary policy and analysts. Specifically, Chapter 2 examines the impact of the central bank's monetary policy surprises on analysts' earnings forecasts. Chapter 3 investigates how analysts interpret the private information embedded in the central bank's monetary policy surprises and incorporate it into their earnings forecasts. Chapter 4 focuses on the role of the analyst in transmitting information across firms and further influencing firms' investment decisions. This chapter explores how this process is affected by analysts' research portfolios. Overall, this thesis contributes to the accounting, finance and macroeconomic literature by extending the understanding of financial analysts from different perspectives.

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Declaration of Authenticity

I, the undersigned, declare that this thesis is original and authentic, and is the result of my own work. This thesis has not been submitted in substantially the same form for the award of a higher degree elsewhere. Except where acknowledged and referenced, all statements and arguments are my own.

I also declare that Chapter 2 and Chapter 3 of this thesis are based on two papers co-authored with Wen Lin, an assistant professor of Central University of Finance and Economics, and Yang Wang, an assistant professor of Lancaster University. For these two chapters, I was responsible for developing the research ideas and questions, designing and conducting empirical analyses, and writing the chapters. The contributions of the co-authors have been limited to the reasonable level expected in a doctoral thesis at a research university in the United Kingdom.

Xiaoyong Wu

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Chapter 1: Introduction

This thesis examines the interaction between sell-side financial analysts, who follow firms and produce forecasts, the central bank, and the external information environment. Specifically, by integrating theories from accounting, finance and economics, it explores the impacts of monetary policy surprises on analysts' earnings forecasts (Chapter 2), how analysts interpret the central bank's private information embedded in monetary policy surprises and incorporate it into their forecasts (Chapter 3), and how the complexity of analysts' portfolios affects their roles in facilitating intra-industry information transfer (Chapter 4). Therefore, the findings of this thesis are relevant to policymakers and regulators.

This thesis chooses to focus on the interplay between sell-side analysts and the central bank for two reasons. First, given the tight connection between the central bank, the local economy and firms' performance, the monetary policy of the central bank is crucial for analysts to do their jobs. Previous studies have documented that, through different channels, monetary policy significantly influences major macroeconomic indicators such as inflation, the real interest rate, and GDP, which are all related to firms' performance (e.g., Bernanke and Gertler, 1995, Kuttner, 2001, Iacoviello and Minetti, 2008).

Furthermore, previous studies have shown that the transmission of the monetary policy is not uniform, leading to heterogeneity in the impacts of monetary policies on firms and financial markets (e.g., Ozdagli, 2018, Armstrong et al., 2019, Ozdagli and Velikov, 2020). As important financial intermediaries, analysts collect, process and disseminate value-relevant information, and by doing this job, they further influence the decisions of other market participants. Therefore, analysts might play a crucial role in the transmission of the central bank's monetary policy.

Second, by accessing different information sources and employing different models, the central bank holds private information about economic fundamentals that is not available to the public (e.g., Romer and Romer, 2000, Lakdawala and Schaffer, 2019). This private information is relevant to analysts for assessing firms. Previous studies show that, after observing the central bank's monetary policy and inferring its related private information, market expectations about monetary policy and economic fundamentals in the future are further shaped and updated (e.g., Lakdawala and Schaffer, 2019, Nakamura and Steinsson, 2018). Collectively, examining the interaction between the central bank and analysts leads to a better understanding of the impact of the central bank's monetary policy on the financial market and market participants.

Apart from its focus on the central bank, this thesis deals with information disclosure and transmission, and particularly how this transmission process is affected by the analysts and their characteristics. There are two motivations for this thesis to focus on this topic. First, the information transmission helps to further understand the economic consequence of the disclosure. There has been a rich set of studies exploring the direct impact of information on disclosing firms, and particularly the firm-level disclosure benefits and costs. For instance, while enhanced information disclosure may lead to lower liquidity risk and a lower cost of capital, and facilitate investments (e.g., Biddle et al., 2009, Ng, 2011, Barth et al., 2013), it also increases proprietary costs and competition costs (e.g., Botosan and Stanford, 2005, Bens et al., 2011).

In addition to the disclosing firms, this information is also relevant to other firms and especially to firms operating in the same industries as the disclosing firms. Seminal papers show that an earnings announcement by one firm affects the share price movements of its industrial peers (e.g.,Clinch and Sinclair, 1987, Han and Wild, 1990). Recent empirical studies use a variety of settings to explore the effects of information disclosure on other firms. One popular strand of this literature investigates the spillover effects of financial misrepresentation on peer firms' share price and real investment decisions (e.g., Xu et al., 2006, Gleason et al., 2008, Durnev and Mangen, 2009, Beatty et al., 2013). These studies show that the economic consequences of information extend beyond disclosing entities. By focusing on information transmission, the understanding of the disclosure effect could be enriched.

Second, by examining different settings, the association between analysts' characteristics and their performance and its related impacts could be understood further. Previous studies have identified a series of relevant analysts' characteristics, such as experience, available resources, and portfolio choice, and explored the impacts of these characteristics on analysts' forecast performance and the financial market (e.g., Clement, 1999, Jacob et al., 1999, Clement and Tse, 2005, Clement et al., 2007). Beyond these direct impacts, analysts' characteristics might play a further role in other contexts. Given the role of analysts as information intermediaries, they could significantly influence the information transmission among firms and markets and therefore affect externalities by influencing the real behaviour of firms. So far, exactly how analysts' characteristics play a role in this process is not fully understood.

This thesis has three self-contained studies that investigate how the central bank's monetary policy influences analysts' earnings forecasts and how analysts affect information transmission across firms. Chapter 2 of this thesis investigates the impact of the central bank's monetary policy surprises on analysts' short-term earnings forecasts. Managing market expectations about monetary policies through communication is important for central banks (Blinder et al., 2008). However, this expectation management often fails in practice, leading to policy misalignment between central banks and market participants, which result in the central bank's monetary policy surprises (e.g., Bernanke and Kuttner, 2005, Armstrong et al., 2019).

The impacts of these monetary policy surprises on analysts' short-term earnings forecasts are unclear. On the one hand, their short-term earnings forecasts might not be affected by these monetary policy surprises. Through different transmission channels, the central bank's monetary policy can indeed significantly influence firms' earnings (e.g., Cukierman and Meltzer, 1986, Bernanke and Gertler, 1995, Kuttner and Mosser, 2002, Melosi, 2017). However, this transmission of the monetary policy from the central bank to the private sector takes time, and may need a half year or even a few years (e.g., Bernanke and Gertler, 1995, Van Els et al., 2001). Thus, even though analysts realize that their expectations about monetary policy are different from actual policy, if they are rational in processing macroeconomic information, these monetary policy surprises may not bias their short-term earnings forecasts.

On the other hand, there are limits to how well analysts can process information. Various studies show that analysts cannot always process financial information correctly, leading to biased forecasts (e.g., Abarbanell, 1991, Abarbanell and Bernard, 1992). The fact that sell-side analysts primarily focus on the firms rather than macroeconomic policies suggests that they may not be good at processing macroeconomic information, thus yielding biased forecasts (e.g., Hope and Kang, 2005, Hugon et al., 2015). In addition to the types of information that analysts draw upon, studies have also shown that uncertainty and task complexity make it more difficult for them to process the information (e.g., Haw et al., 1994, Zhang, 2006). Apart from the analyst literature, the macroeconomic literature argues that due to the unique position of the central bank in a local economy, it can cause market participants to place too much weight on the central bank's information and distort their behaviour (Amato et al., 2002, Morris and Shin, 2002). Taken together, if the analysts are irrational in processing macroeconomic information, these monetary policy surprises can bias their short-term earnings forecasts.

This association between monetary policy surprises and analysts' forecasts could be influenced by central banks' disclosure strategies. While some studies emphasize the benefits of transparent disclosure (e.g., providing clear guidance and offering a justification for policy choices, etc.) in guiding market expectation (e.g., Blinder et al., 2008), others identify the detrimental impacts it may have on market participants (e.g., Morris and Shin, 2002, Ehrmann and Fratzscher, 2009). Furthermore, the reporting quality of firms might also play a crucial role in this association. Poor reporting quality can mask the true economic underlying of the firms, making it difficult for analysts to assess the impacts of monetary policy surprises.

Using the Fed's monetary policy surprises as a proxy for the misalignment of the monetary policy between the central bank and market participants, this chapter finds that policy surprises bias analysts' short-term earnings forecasts and these biased forecasts are mainly due to expansionary monetary policy surprises. Moreover, the results of biased forecasts are mainly driven by the surprises having persistent impacts, the surprises from FOMC meetings reversing direction in monetary policy, and the surprises from unscheduled FOMC meetings.

Next, this chapter finds that improved FOMC post-meeting disclosure could bias analysts' forecasts. Finally, it finds that firms with poor reporting qualities drive the results of biased forecasts. Overall, the findings of this chapter outline the influential impacts which the central bank's monetary policy surprises have on financial analysts.

Chapter 2 contributes to the literature on central banks by investigating the impact of monetary policy surprises on analysts (e.g., Woodford, 2005, Blinder et al., 2008). It then extends the analyst literature by examining the association between central bank monetary policy, which is one important macroeconomic factor still to be fully explored, and analysts (e.g., Basu et al., 2010, Hope and Kang, 2005, Hugon et al., 2015). It also contributes to the literature on the interaction between macro-level information and micro-level entities (e.g., Konchitchki and Patatoukas, 2014, Armstrong et al., 2019). Finally, this chapter adds to the literature by investigating the information used in formulating the analysts' forecasts (e.g., Lang and Lundholm, 1996, Hutton et al., 2012).

Chapter 3 investigates the central bank's private information. The central bank holds private information about the economic fundamentals, and this private information is relevant to market participants. Especially for the analysts, who collect and process information to produce forecasts, this private information held by the central bank could help them to assess firms' performance. This chapter examines how analysts interpret the central bank's private information and incorporate it into their forecasts. Given that the transmission of monetary policy takes time, if the analysts are rational (irrational) in processing information and making short-term earnings forecasts, theories of information effects (monetary policy transmission) should dominate the interpretation of this private information.

Using the private information embedded in the Fed's monetary policy surprises, this chapter finds that the analysts' interpretations of the Fed's private information are asymmetric. Specifically, they follow conventional theories of monetary policy transmission (theories of information effects) to interpret expansionary (contractionary) monetary policy revealed by the Fed's private information and revise their forecasts. Consistent with the findings of Chapter 2, this chapter also finds that the analysts are irrational in dealing with expansionary monetary policy. Next, it finds that task-specific experience from past FOMC meetings makes analysts support the conventional theories of monetary policy transmission. Finally, this chapter finds that investors rely more on analysts in the light of the Fed's private information, supporting the role of analysts in transmitting central bank monetary policy. Collectively, the results presented in this chapter indicate the interaction between the central bank and financial analysts.

Chapter 3 contributes to the literature on central bank information and especially to previous studies exploring the impact of central bank's private information (e.g., Romer and Romer, 2000, Lakdawala and Schaffer, 2019). The findings of this chapter show that analysts revise their earnings forecasts to incorporate the private information embedded in the Fed's monetary policy surprises. Next, this chapter responds to the call for understanding the heterogeneity in the transmission of monetary policy by examining the market response to analysts' forecast revisions in the light of the Fed's private information, and adds to the literature on the interaction between the central bank's monetary policy, financial market and firms' performance (e.g., Gertler and Gilchrist, 1994, Ozdagli, 2018, Armstrong et al., 2019). Finally, this chapter adds to the literature on the effects of analysts' characteristics by examining the task-specific experience (e.g., Clement, 1999, Mikhail et al., 1997, Clement et al., 2007).

Chapter 4 of this thesis investigates the impact of analysts' characteristics on their role in transmitting restatement information within the industry. Previous studies have explored analysts as an important mechanism that facilitates intra-industry information transmission by focusing on analyst coverage and following (Hilary and Shen, 2013). This chapter extends the studies on information transmission via analysts by exploring peer firms' investment decisions subsequent to other firms' accounting restatements, conditional on whether the peer firms are followed by thorough or less thorough financial analysts.

Empirical results show that after other firms' restatement announcements, peer firms further reduce their investments if they are followed by thorough analysts whose research portfolios are less complex. This shows that thorough analysts transmit restatement information effectively and affect peer firms' investments. Furthermore, cross-sectional tests show that results are mainly driven by firms with a higher probability of having distorted investments. Finally, findings from the event study show that investors react to analyst forecast revisions subsequent to the restatement announcement, and particularly to those made by thorough analysts. Taken together, these empirical findings show that thorough analysts transmit restatement information and influence peer firms' investments by fulfilling their role of external firm monitor and changing investors' perceptions of peer firms.

Chapter 4 contributes to the studies of analysts as an important mechanism for transmitting information within the industry (e.g., Beatty et al., 2013, Hilary and Shen, 2013, Martens and Sextroh, 2021) by showing that thorough analysts facilitate intra-industry information transfer. Furthermore, this chapter adds to the studies of analysts playing the role of external firm monitor (e.g., Yu, 2008, Irani and Oesch, 2013) by using the setting of other firms' accounting restatements, which is not predicted by the peer firms and their analysts. Finally, it complements the literature on analyst portfolio choice (e.g., Clement, 1999, Drake and Myers, 2011), by showing that the impact of portfolio choice goes beyond analyst forecasting activity and has real effects on firms' investments.

The remainder of this thesis proceeds as follows. Chapter 2 examines the impact of the central bank's monetary policy surprises on analysts' earnings forecasts. Chapter 3 explores how analysts interpret and incorporate the central bank's private information. Chapter 4 investigates how restatement information transmission through analysts is affected by their portfolio choices. Chapter 5 concludes.

Chapter 2: Central Bank Policy Surprises and Biased Forecasts of Analysts[1]

2.1. Introduction

Managing the expectations of financial market participants about monetary policy and ensuring they are the same as actual policy has been viewed by the central bank as a critical task. However, both academic research and anecdotal evidence show that market participants often misalign with the central banks, leading to monetary policy surprises in the financial markets (Blinder et al., 2008).[2] These policy surprises might influence the forecasting behaviour of sell-side analysts, who play a crucial role in processing and disseminating information. However, no comprehensive evidence of such impacts has been documented. Relying on the Federal Open Market Commission (FOMC) monetary policy meetings, this chapter investigates whether and how monetary policy surprises affect the earnings forecasts of analysts.

Central bank monetary policy can significantly affect firms' earnings through different transmission channels (e.g., Hugon et al., 2015, Ozdagli, 2018).[3] Because of its material impact on firms' earnings, the central bank monetary policy rate is viewed by market participants, including analysts, as a major indicator of macroeconomic conditions.[4] Before the central bank discloses the monetary policy rate, market participants usually form expectations about the monetary policy rate (e.g., Kuttner, 2001,

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[1] This chapter is based on the working paper "Central Bank Expectation Management and Analyst Forecast Performance" co-authored with Wen Lin and Yang Wang. The paper has been presented in the seminars of the Central University of Finance and Economics, the University of Bristol, and the 2023 FARS Midyer Meeting.

[2] For instance, "[T]he message sent by investors in stormy financial markets is clear: the global economic expansion could be in trouble. But the Federal Reserve remains optimistic, publishing strong growth forecasts for the U.S. and plotting out more interest rate rise (*Financial Times*, 30th December, 2018)." In addition to anecdotal evidence, empirical studies have provided quantitative evidence of this misalignment between central banks and market participants (e.g., Kuttner, 2001, Bernanke and Kuttner, 2005, Lakdawala and Schaffer, 2019).

[3] Following conventional theories of monetary policy transmission, such as the credit and balance sheet channel, expansionary (contractionary) monetary policy can boost (damage) firms' earnings by making them access more (less) credits, incur lower (higher) interest expenses, earn higher (lower) revenue, and incur lower (higher) external financing premium (e.g., Bernanke and Gertler, 1995).

[4] For instance, anecdotal evidence can be found in newspaper such as "U.S. stock markets fell sharply for a second session on Wednesday after the Federal Reserve indicated it was finished with rate-cuts…an analyst downgrade knocked Nucor 4.8 per cent to $76.01. (*Financial Times*, 21st May, 2008)". "Wall Street analysts have taken an axe to profit forecasts for the biggest U.S. banks, fearing that the U.S. Federal Reserve…will hold off on pushing up interest rate (*Financial Times*, 10th July, 2016)". "A sharp increase in interest rates to tame fresh inflation shocks would pose a risk to the American economy… businesses also facing higher delinquencies, bankruptcies and other forms of financial distress (*Financial Times*, 9th May, 2022)"

Bernanke and Kuttner, 2005) and make trading decisions on the basis of their expectations (Armstrong et al., 2019). This market expectation plays a key role in the implementation of monetary policy in real economies, such as intermediate and long-term interest rates (Eggertsson and Woodford, 2003, Bernanke et al., 2004, Blinder et al., 2008). Market expectations can be influenced by central bank communication. Through different communication channels, the central bank can shape market expectations in relation to future policy rates and paths (Woodford, 2005, Blinder et al., 2008). Thus, for central bankers, managing the expectations of market participants and ensuring that they are aligned with the central bank are necessary to implement their monetary policy effectively (Bernanke et al., 2004, Blinder et al., 2008).

The importance of expectation management has been widely recognized by central banks, and in practice it is never an easy task. The optimum strategies and communication levels are still under debate (e.g., Woodford, 2005, Ehrmann and Fratzscher, 2007, Blinder et al., 2008). Previous studies have well documented that central banks often fail to manage market expectations. For instance, by using the changes in Fed funds futures rate around the FOMC meetings as a measure of the market expectation about the Fed funds rate (hereafter, FFR), cases of market expectations not being the same as actual monetary policies are evident in practice (e.g., Kuttner, 2001, Bernanke and Kuttner, 2005, Gorodnichenko and Weber, 2016, Armstrong et al., 2019). Such ineffective expectation management leads to monetary policy surprises in the financial market.

Though the central bank's monetary policy has an influence on the local economy, it is an open question whether monetary policy surprises can affect the earnings forecasts of analysts. On the one hand, it takes time for the impact of the monetary policy to affect the private sector, and this may be six months or even a few years (e.g., Bernanke and Gertler, 1995, Van Els et al., 2001). This means that firms' short-term earnings should not be affected by the monetary policy immediately. If analysts are rational in processing the macroeconomic information, they should be aware that the policy transmission is time-consuming and so their short-term earnings forecasts should not be biased by the monetary policy surprise.

On the other hand, this monetary policy surprise might bias analysts' short-term earnings forecasts if they are irrational in processing the information. There are limits to how well analysts can process information. Previous studies have clearly shown that analysts cannot always correctly process firm-related information, such as stock price changes and earnings news (e.g., Abarbanell, 1991, Abarbanell and Bernard, 1992). Apart from the financial information, sell-side analysts have no macroeconomic expertise and are not good at processing macroeconomic information such as GDP, inflation and foreign exchange, and this has a detrimental impact on their performance (e.g., Hope and Kang, 2005, Hugon et al., 2015). Furthermore, due to the unique position of the central bank in a local economy, the information it disclosed is the focal point and it can therefore crowd out other sources of information (Amato et al., 2002, Morris and Shin, 2002), and this makes analysts place too much weight on monetary policy information. Consequently, monetary policy surprises might bias analysts' forecasts.

To examine the impact of the central bank's monetary policy surprise on analysts' earnings forecasts, the surprise component of the FFR is used. Following prior studies (e.g., Kuttner, 2001, Bernanke and Kuttner, 2005, Armstrong et al., 2019), the FFR surprises are measured as the changes in the Fed funds rate futures contracts around FOMC announcements and multiplied by -1. Therefore, a positive (negative) surprise reflects an unexpected decrease (increase) in FFR, suggesting an expansionary (contractionary) monetary policy.[5]

The empirical analysis presented in this chapter is based on the quarterly earnings forecasts for firms from 1989 to 2008, during which there were 176 FOMC meetings. The period from which this sample is taken ended in 2008 because this was the last year in which the Fed used the target FFR as its main policy instrument.[6] To examine the effects of FFR surprises on analysts' forecasts, the regression of the proportional mean absolute forecast error on the absolute FFR surprise from the most recent FOMC meeting is estimated. The results show that larger FFR surprises are associated with more biased

[5] The FFR surprise can be 0. This implies that the market expectation about monetary policy is aligned with the central bank.

[6] The Fed switched from disclosing a target rate to disclosing a range for the rate, and used unconventional monetary policy tools (e.g., quantitative easing) after 2008. The decision to end test samples in 2008 is consistent with prior studies (e.g., Gallo et al., 2016, Ozdagli, 2018).

analysts' forecasts. In particular, a 1% increase in the Fed's monetary policy surprises leads to a 4.88% increase in analysts' proportional mean absolute forecast errors.

Furthermore, signed forecast errors and signed FFR surprises are used. The results show that biased forecasts are due to forecast earnings being larger (smaller) than actual earnings when analysts view the monetary policy surprises as good news (bad news) for the firms.[7] As well as this, FFR surprises are divided into positive (i.e., expansionary) and negative (i.e., contractionary), and this chapter finds that these biased forecasts are caused by expansionary FFR surprises. These results indicate that analysts are more sensitive to expansionary policy than contractionary policy.[8] Overall, the findings of this section indicate that the Fed's monetary policy surprises make analysts produce biased forecasts.

This chapter next explores whether these biased forecasts vary across different types of FFR surprises. First, it distinguishes between monetary policy surprises that affect market expectations of future interest rates and those that only affect the timing of rate changes. In this analysis, FFR surprises are categorized into those which are viewed by markets as changing the expected policy path in the following months (i.e., level surprises) and those that are regarded merely as timing differences in having information on current monetary policy (i.e., timing surprises). The results of further splitting FFR surprises and re-running the regression show that biased forecasts are mainly caused by level surprises. These results indicate that analysts respond strongly to monetary policies that have a persistent impact on the economy.

Second, this chapter analyses the impact of the direction of actual FFR changes on analysts' earnings forecasts. There have been 8 FOMC meetings that reversed the direction of actual FFR changes compared with the previous meetings. Such turning-point meetings are expected to have a larger impact on the future economy than other "usual" meetings and elicit a larger response (Bernanke and Kuttner, 2005). The regression model

[7] Due to the fact that the impact of the monetary policy on firms' performance is mixed, Chapter 2 does not define what monetary policy surprises are viewed by analysts as good or bad news. Instead, Chapter 3 of this thesis will examine analysts' interpretation of monetary policy surprise.

[8] The finding that responses to the Fed's contractionary monetary policy are insignificant is consistent with previous studies (e.g., Gallo et al., 2016, Armstrong et al., 2019).

includes interactive dummies for turning-point meetings with FFR surprises and finds that these meetings significantly exacerbate the analysts' biased forecasts.[9]

Third, this chapter distinguishes between FFR surprises that occurred in scheduled and in unscheduled FOMC meetings. In contrast to scheduled meetings, unscheduled meeting calendars are not available to the public in advance.[10] These unscheduled meetings may convey a sense of urgency about the economy. This further exploration shows that the policy surprises from unscheduled FOMC meetings have a significant impact on analysts, yielding biased forecasts.

Furthermore, this chapter investigates how these biased forecasts of analysts vary with the Fed's communication strategies. The Fed has mandated disclosure of target FFR explicitly through the post-meeting statement since 1994. Hence, this chapter examines the impact of the Fed's revised communication on analysts' forecasts by considering the pre-1994 and post-1994 periods separately. This shows that biased forecasts are mainly driven by post-1994 FOMC meetings, suggesting that transparent central bank communication might not be ideal for the financial markets (e.g., Morris and Shin, 2002, Ehrmann and Fratzscher, 2007). Additionally, this chapter finds that, although greater efforts were made to further improve post-meeting disclosure between 1997 and 2002, this was unable to improve analysts' biased forecasts.[11]

Finally, this chapter further examines whether the reporting qualities of firms can affect analysts' earnings forecasts. Previous studies have shown that the reporting qualities of firms are associated with analysts' forecast performance (e.g., Hope, 2003, Chen et al., 2015a). Poor reporting quality (e.g., managing earnings) could mask the true underlying activities and performance of firms, and analysts therefore find it difficult to collect past earnings information to assess the impact of monetary policy surprises on firms, leading to biased forecasts. Consistent with this prediction, this chapter finds that

[9] Apart from that, there have been 20 FOMC meetings that the FFR surprises changed from 0 to expansionary, and 9 FOMC meetings that the FFR surprises changed from 0 to contractionary. Alternatively, if turning-point meetings are defined as those in which the FFR surprises changed from 0 to expansionary or contractionary, the results are qualitatively similar.

[10] Generally, the FOMC hosts 8 scheduled meetings each year and the meeting schedules are available to the public in advance. However, as a necessary response to economic and financial conditions, the FOMC may also host unscheduled meetings.

[11] For more detailed information on changes in FOMC post-meeting disclosure, please see Table 2.7.

FFR surprises lead to biased forecasts when analysts follow firms with high absolute discretionary accruals or high absolute current accruals (i.e., low reporting quality).

This chapter makes three contributions to the literature. First, it contributes to the literature on central banks by examining how monetary policy surprise affects sell-side analysts (e.g., Bernanke and Reinhart, 2004, Woodford, 2005, Blinder et al., 2008). The results of this chapter indicate that monetary policy surprises associated with the Fed's communication strategies could significantly influence the accuracy of analysts' forecasts. These findings document the importance of central bank expectation management (e.g., Cukierman and Meltzer, 1986, Sibert, 2006, Crowe and Meade, 2008, Ehrmann and Fratzscher, 2009).

Second, it adds to the literature that examines the impact of macroeconomic factors on analysts' earnings forecasts by using the unexpected FFR change. Findings that biased forecasts may be due to the Fed's monetary policy surprises add to the literature on the association between financial analysts and crucial macroeconomic factors (e.g., Basu et al., 2010, Hope and Kang, 2005, Hugon et al., 2015). Furthermore, it also contributes to the literature on the interaction between macro-level entities and micro-level entities. In contrast to studies on linking micro-level information to macro-level information (e.g., Konchitchki and Patatoukas, 2014, Gaertner et al., 2020), this chapter focuses on the transmission of macro-level information to micro-level entities (e.g., Ozdagli, 2018, Armstrong et al., 2019, Ozdagli and Velikov, 2020).

Third, this chapter extends our understanding of the information used in formulating analysts' earnings forecasts. The findings show that analysts cannot correctly process the information on central bank monetary policy, leading to biased forecasts. These biased forecasts are particularly significant when firms' reporting quality is low. These results provide new insights into how analysts use information in their forecasts (e.g., Lang and Lundholm, 1996, Hutton et al., 2012).

This chapter proceeds as follows: section 2.2 provides theoretical underpinnings and predictions; section 2.3 outlines the selection of data; section 2.4 discusses the main research design; section 2.5 reports the results and findings, and section 2.6 concludes.

2.2. Theoretical underpinning and hypothesis

2.2.1 Central bank monetary policy

In most countries, the primary policy goal of central banks is to implement appropriate monetary policies to control inflation and maintain financial stability (Bank for International Settlements, 2009). To achieve this policy goal, central banks use different types of policy instruments. This chapter focuses primarily on open market operations by the Fed in the form of the purchase and sale of securities to reach a target FFR, except for the period from December 2008 to December 2015 when the FFR reached the "zero lower bound".[12] The FOMC sets the Fed's target FFR in 8 regular meetings per year (i.e., scheduled meetings). However, the FOMC may arrange additional meetings to adjust the target FFR as a necessary response to the economic conditions (i.e., unscheduled meetings). Through these open market operations, the Fed significantly affects the short-term interest rate.

The central bank's monetary policy can be transmitted to the private sector and ultimately influence firms' earnings. In recent years, the credit channel of monetary policy transmission has attracted the most attention.[13] This credit channel includes two sub-channels, namely the bank lending channel and the balance sheet channel. The bank lending channel shows that an expansionary (contractionary) monetary policy increases (reduces) the supply of loans to other commercial banks and, thus, influences firms' financing and earnings.[14] The balance sheet channel indicates that expansionary

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[12] The other two main instruments are: 1. The discount rate of short-term loan to depositionary institution; 2. The requirement of the reserve which banks must maintain by themselves or with the Fed. After the FFR reached 0% after the Global Financial Crisis of 2008, the Fed also began using interest on required reserve balances and overnight purchase as additional policy tools (for more details, please see: https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/the-federal-reserves-new-approach-to-raising-interest-rates-20160212.html)

[13] In addition to the credit channel, the central bank monetary policy can also influence firms' earnings through the traditional interest rate (e.g., Kuttner and Mosser, 2002). This particular channel assumes no market friction. However, deviations from this critical assumption are evident in the real world due to the imperfect information in the market (Bernanke and Gertler, 1995).

[14] The bank lending channel assumes the critical role of the banks of alleviating the information asymmetry between firms and capital providers, and constrains the ability of the bank to replace its lost deposit. However, given the fact that the supplier of marginal credits, sources of loanable funds and bank lending channels have changed since the deregulation and innovation in the banking industry (e.g., Bernanke and Gertler, 1995, Woodford, 2010, Drechsler et al., 2017), this assumption might not have held fully in the

(contractionary) monetary policy increases (reduces) the net income and net worth of firms, thereby boosting (reducing) firms' earnings via the external financing premium (e.g., Bernanke and Gertler, 1995, Mishkin, 1995). Although the impacts of monetary policy are influential, transmission to the private sector takes time. As documented in previous studies, it may take up to 6-12 months for the monetary policy to affect the local economy and the peak effects occur even later (e.g., Bernanke and Gertler, 1995, Van Els et al., 2001).

Over the past decade, effective control of the overnight interest rate has not been the only criterion for judging the success of monetary policy. Instead, managing market participants' expectations of long-term interest rates is more important. Blinder (1998) argues that managing market expectations of central bank actions is also the essence of monetary policy. Guiding market expectations so that they remain in line with the central bank can facilitate the implementation of monetary policy. This view has become widespread among central bankers (Woodford, 2001). Therefore, expectation management through central bank communication is valuable for the effective implementation of monetary policy.

By using formal types of communication (e.g., official press releases, forward guidance) and informal communication channels (e.g., speeches, interviews), central banks can disclose objectives, strategies, policy decisions, economic outlook and future policy paths to the public (Blinder et al., 2008). This information disclosure can help market participants understand a central bank's policy stance and further shape their expectations. Extensive evidence has shown that central bank communication can guide the direction of the financial markets (Ehrmann and Fratzscher, 2007, Brand et al., 2010) and improve the market prediction of the interest rate decision (De Haan, 2008).

Aiming to improve its expectation management, the Fed has adjusted its communication and disclosure strategies since the 1990s. The milestone in these adjustments was in February 1994 when the FOMC first started announcing its decisions on the target FFR.[15] These real-world developments have spawned a huge academic

U.S. in recent years.

[15] Prior to 1994, the financial market had to infer the current target FFR on the basis either of the open

literature on central bank communication. Some studies argue that central bank communications "*create news*" and "*reduce noise*" in financial markets, as market participants make more efficient decisions when they can correctly predict central bank actions (Poole, 2001).

Though central bank communication might bring benefits, other studies raise one major concern about the appropriateness of the communication, e.g., how much they should disclose, in what form, and how often. First, the theoretical papers fail to reach a consistent conclusion about the optimal level of central bank communication (e.g., Geraats, 2002, Morris and Shin, 2002, Van der Cruijsen and Eijffinger, 2010). Talking more is not always better. Second, recent empirical evidence shows that central bank communications bring unexpected volatility and speculation to the financial markets (Ehrmann and Fratzscher, 2009)[16].

There is substantial evidence of failed central bank expectation management in practice. Figure 2.1 shows the stock market in response to the Fed's monetary policy surprise. On the 27th April 2006, markets misinterpreted comments by Federal Reserve Chairman Mr. Bernanke to mean that the Fed may take a break from its steady series of interest rate rises in the next FOMC meeting. As a result, Standard & Poor's 500 stock index, the Dow Jones industrial stock index and the Nasdaq Stock Market composite index rose immediately. However, on the 10th May 2006, in the next FOMC meeting, the Fed continued to raise the interest rates, which was the opposite of what the market expected and this monetary policy surprise led to a significant decline in all stock indexes.

[Insert Figure 2.1]

Notwithstanding that central bank communication has improved remarkably in recent decades, it is still far from ideal. As reported in studies of market responses to disclosures of monetary policy, market expectations about monetary policy are not often in line with the central banks (e.g., Kuttner, 2001, Gorodnichenko and Weber, 2016,

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market operation conducted by the Fed or press releases of the discount rate. The current target FFR is disclosed after the next FOMC meeting (e.g., Bernanke and Kuttner, 2005, Ehrmann and Fratzscher, 2005).

[16] For instance, based on the Fed's disclosure, an analyst of Standard Charted stated that "The Federal Reserve's pension fund asset allocation appears to reflect the Fed's caution about the reflation trade: it seems to underweight equities" (*Financial Times*, March 30, 2017). However, given the natural of the Fed pension management, this argument hardly holds in reality.

Armstrong et al., 2019). This chapter finds that market participants' expectations about the Fed's FFR have been different from the target FFR in 122 out of 176 FOMC meetings from 1989 to 2008. This misalignment between central banks and market participants indicates that monetary policy surprises could further influence the behaviour of market participants.

2.2.2 Monetary policy surprises and the earnings forecasts of analysts

Monetary policy is crucial to analyst forecasts. Figure 2.2 shows that EVERCORE ISI, an investment advisory firm, released a forecast of Ford Motor's performance on the day after the FOMC meeting that occurred on the 4th May 2022. In this forecast, the monetary policy hit the headlines, and analysts said that "we are not blind to the impact of the Fed…". Although the importance of monetary policy is evident, when analysts find that their expectations about monetary policy are not the same as the actual monetary policy, it is not certain whether this policy surprise will affect analysts' earnings forecasts, and particularly their short-term earnings forecasts.

[Insert Figure 2.2]

Figure 2.3 demonstrates the theoretical framework of the impacts of the central bank's monetary policy surprises on analysts' earnings forecasts. On the one hand, a monetary policy surprise might not influence analysts' earnings forecasts. As documented in the macroeconomic literature, while a central bank's monetary policy has an influence on the local economy (e.g., Bernanke and Gertler, 1995, Mishkin, 1995), the transmission of its impacts to the private sector needs a certain amount of time, ranging from half a year to a few years (e.g., Van Els et al., 2001). If analysts are rational in processing the macroeconomic information, they should be aware that, though the actual monetary policy is different from what they originally expected, this monetary policy surprise is unlikely to affect firms' short-term earnings immediately. Consequently, the analysts' short-term earnings forecasts will not be biased by the central bank's monetary policy surprise.

[Insert Figure 2.3]

On the other hand, if the analysts are irrational in processing the macroeconomic information, the central bank's monetary policy is likely to affect their short-term earnings forecasts. Previous studies have shown that analysts are limited in their ability to process information (e.g., Elliot et al., 1995, Abarbanell and Bushee, 1997). Though the role of sell-side analysts is to process information and produce research outputs, the literature has shown that they cannot always process information correctly and produce unbiased forecasts. In relation to financial information such as earnings or stock prices, studies have documented that analysts' ability to process relevant information is limited, yielding biased forecasts (Lys and Sohn, 1990, Abarbanell, 1991, Abarbanell and Bernard, 1992, Ali et al., 1992).

Apart from financial information, given that sell-side analysts are not macroeconomic specialists, it is even harder to believe that they can process macroeconomic information rationally. Previous studies have shown that it is difficult for analysts to process information on GDP, inflation or foreign exchange, leading to biased forecasts (e.g., Hope and Kang, 2005, Hugon et al., 2015). Furthermore, the literature also shows that analysts' forecasts are further influenced by certain crucial factors, including uncertainty and task complexity (e.g., Haw et al., 1994, Zhang, 2006, Amiram et al., 2018). In general, it is reasonable to believe that analysts' forecasts could be affected by the central bank's monetary policy.

Apart from that, because of the unique position of the central bank in a local economy, the information it discloses is the focal point for the beliefs of the market participants (Amato et al., 2002, Morris and Shin, 2002). Analysts might place too much weight on the information of the central bank and crowd out other sources of information. This is because the prevailing conventional wisdom is that the key economic indicators (i.e., GDP, outputs, and unemployment rate, etc.) are linked to the target policy rate, which is determined by the central bank. The analysts might thus produce biased forecasts as a response to the central bank's monetary policy surprise. Two competing hypotheses can therefore be proposed:

H1a: Analysts' short-term earnings forecasts will not be biased by the central bank's monetary policy surprise.

H1b: Analysts' short-term earnings forecasts will be biased by the central bank's monetary policy surprise.

2.3. Sample selection

Table 2.1 shows the sample selection procedure. The sample period began in 1989 as the federal funds futures market was established in 1989 at the Chicago Board of Trade, and this chapter needs federal funds future rate to measure monetary policy surprises. The target federal funds rate was the explicit policy instrument until the zero lower bound took over after the financial crisis[17], and therefore the sample ended in 2008. On the one hand, this chapter recognizes that the sample period is not the most recent, and this choice to some extent limits how far the findings can be generalized. On the other hand, ending the sample in 2008 can maintain sample consistency and reduce the noise from different types of monetary policy and disclosure mechanism.[18] Furthermore, following Bernanke and Kuttner (2005), the FOMC meeting on 17th September 2001, which was an unscheduled meeting that was held after the 9/11 terror attacks, is excluded.

The analyst forecast and actual earnings data were obtained from the I/B/E/S Detail File. To be included in the sample, analysts must issue earnings forecasts in U.S. dollars, with no missing data for analysts' identifiers, analysts' forecasts and actual earnings. Figure 2.4 shows the timeline for selecting analysts' forecasts. To examine the response of analysts' short-term earnings forecasts to monetary policy surprises, this chapter focuses on analysts' one-quarter ahead earnings forecasts issued after the most recent FOMC meeting (i.e., FOMC at t) and before the next FOMC meeting (i.e., FOMC at $t+1$). If more than one forecast is issued after the most recent FOMC meeting, the first forecast is selected.[19] These selected forecasts can be the revised forecast for a firm made by an

[17] Electively in 2009, the Fed replaced the target FFR by using the large-scale purchases of Treasury and agency securities (i.e., "quantitative easing") as its primary policy tool in response to the global financial crisis in 2008. The sample ends in June 2008 before the occurrence of the financial crisis to avoid the high uncertainty during this period, even though the main policy pool at that moment was the target FFR.

[18] Compared with the sample period of this chapter, the Fed has used unconventional monetary policy tools (i.e., quantitative easing) since 2009 and used the target funds rate range since the end of 2008.

[19] For instance, the FOMC hosted meetings on 2nd February 2000 and 21st March 2000. During the period between these two meetings, an analyst *i* issued two earnings forecasts with forecast period ended on 31st March 2000 for firm *m*. The first earnings forecast is selected for analysing the impact of the monetary policy surprise from the FOMC meeting on 2nd February 2000.

analyst after the most recent FOMC meeting or the first forecast for a firm made by an analyst after the most recent FOMC meeting. The sample also retains firms with stock price data from CRSP, other analysts-related information from I/B/E/S, and financial statement data from Compustat. Given that the effect of monetary policy on financial firms and utilities could be compounded by other regulation policies, these two types of firms are excluded from the sample. Finally, the sample includes analysts' forecasts made before the current actual earnings announcement dates.[20] This sample selection leaves 1,004,953 firm-quarter observations.

[Insert Figure 2.4 and Table 2.1]

2.4. Research design

2.4.1 Measuring monetary policy surprises

In this chapter, monetary policy surprises are measured by following the method of Kuttner (2001) and Bernanke and Kuttner (2005), who measure the unexpected changes in the FFR around FOMC announcement dates using the expectations embedded in the current federal funds futures contracts. In particular, federal funds futures capture the market's expectations about the Fed's actions. Daily changes in the trading prices of these futures contracts between the FOMC announcements date and the previous trading day serve as a measure of the change in the Fed's policy that is unanticipated by the market.[21]

This daily surprise (*Surprise*) is defined as the measure of monetary policy surprise. See Appendix 2.2 for details on the construction of this variable. To make this signed monetary policy surprise intuitive to be interpreted, the unexpected change in the FFR is multiplied by -1. Therefore, a positive (negative) surprise indicates an unexpected reduction (increase) in the FFR, suggesting an unexpected expansionary (contractionary) monetary policy. Furthermore, the absolute value of surprise is employed, meaning that a larger value implies that the FFR surprise is more significant.

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[20] The current actual earnings announcement dates can be before or after the next FOMC meeting (i.e. FOMC at $t+1$).

[21] If the information with regard to the Fed's policy is fully captured by the market, the daily changes in federal funds futures around FOMC announcement dates will be 0.

2.4.2 Model specification

The analyst forecast error (*FE*) is defined as actual earnings per share (*EPS*) minus the analysts' forecasts, scaled by the price at the beginning of the quarter. Both forecast error and FFR surprise are expressed as percentages. This chapter starts by examining analysts' forecasts with respect to monetary policy surprises by regressing the absolute forecast errors on the absolute monetary policy surprises from the most recent FOMC meetings.[22] Specifically, the proportional mean absolute forecast error (*PMAFE*) is used to further control for the difference in the firm, time and industry (e.g., Clement, 1999, Ke and Yu, 2006). The *PMAFE* is the difference between absolute forecast error for an analyst's forecast of a firm and the mean absolute forecast error for a firm, scaled by mean absolute forecast error for a firm. This chapter also uses the signed forecast errors (*FE*) and signed monetary policy surprise (*Surprise*) to further explore the direction of these biased forecasts. Specifically, based on the above arguments, the following regression model is estimated:

$$\begin{aligned} PMAFE(or\ FE) &= \beta_0 + \beta_1 \cdot Abs\ Surprise(or\ Surprise) + Analyst\ Controls \\ &+ Broker\ Controls + Firm\ Controls + Macro\ Controls + \gamma_t + \theta_j \\ &+ \varepsilon_0 \qquad (2.1) \end{aligned}$$

Following previous papers (e.g., Hugon et al., 2015), there are four classes of controls in the regression model. First, there are analyst-specific variables that are associated with forecast error, including forecast horizon (*HORIZON*), the number of industries covered (*NIND*), number of firms covered (*NFIRM*), and firm-specific experience (*FEXP*). Second, the regression model uses broker firm size (*BSIZE*) to capture the effect of broker-related information on the analysts' forecast performance. Third, the regression model controls for firm-specific variables that affect the forecast error, including total accruals (*LAG_TACC*), annual profitability (*LAG_PROFIT*), and firm size (*LAG_SIZE*).

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22 The median period between analysts' forecast date and the most recent FOMC meeting dates is 22 days. To alleviate concerns that the results might be affected by the next FOMC meeting, the sample is further constrained by the fact that the analysts' forecasts must be made within 22 days of the most recent FOMC meetings and the main results still hold. Alternatively, after including an additional control variable, namely the length of time between the analysts' forecast dates and the most recent FOMC meetings dates in the regression model, the main results still hold.

Fourth, the regression model controls for macroeconomic factors, including inflation rate (*LAG_INFLATION*) and GDP (*LAG_GDP*). All continuous variables are winsorized at the top and bottom 1 percent, and detailed definitions of all variables are included in Appendix 2.2. The regression model also includes year fixed effects, γ_t, and firm fixed effects, θ_j. The regression model is estimated by using OLS regression and standard errors are clustered by firm.

For the regression of proportional mean absolute forecast errors on the absolute FFR surprise, the coefficient on *Abs_Surprise*, β_1, is expected to be positive and significant, suggesting that the FFR surprises worsen analysts' earnings forecasts. As for the regression of signed forecast errors on the signed FFR surprise, a negative (positive) coefficient on *Surprise*, β_1, suggests that forecast earnings are larger (smaller) than actual earnings when analysts view the FFR surprises as good news for firms, or forecast earnings are lower (larger) than actual earnings when analysts view the FFR surprises as bad news for firms. This chapter does not define which monetary policy surprise is viewed by the analysts as good or bad news for the firms. Chapter 3 will examine how analysts perceive and interpret these monetary policy surprises in more detail.

2.5. Results

2.5.1 Descriptive statistics

Panel A in Table 2.2 presents descriptive statistics for the Fed's monetary policy surprise (*Surprise*) in the analysis. There are 176 FOMC meetings held during the sample period, including scheduled and unscheduled meetings. Of the 176 meetings, 77 release unexpected expansionary news to the capital market with positive monetary policy surprises, and 45 release unexpected contractionary news to the market with negative monetary policy surprises. The remaining 54 meetings do not issue surprise rate changes to the capital market. The mean values of *Surprise* for total observations, positive surprise and negative surprise are 0.03%, 0.10% and -0.05%, respectively.[23] Considering that the

[23] For comparison, the mean values of actual changes in target FFR from FOMC meetings for the samples

mean value of the actual changes in target FFR for total observations is 0.04%, the mean value of *Surprise* for total observations indicates that the cases in which market expectations about monetary policies are not the same as the Fed's actual monetary policies are evident in practice. Relatively, the divergence between market participants and the Fed is more significant in the case of unexpected expansionary policy than contractionary policy.

Panel B in Table 2.2 presents descriptive statistics for the key variables in the tests separately after positive and negative surprises. The proportional mean absolute forecast errors (*PMAFE*) of the expansionary sample are larger than others, indicating that analysts produce more biased forecasts under expansionary monetary policy. The negative mean forecast errors (*FE*), either for a positive or negative surprise, show that analysts are on average optimistic. Descriptive statistics for these control variables for positive and negative shocks look similar.

[Insert Table 2.2]

2.5.2 Multivariate results

Table 2.3 column 1 reports the results of the regressions of Eq. (2.1) by using the absolute forecast error and absolute FFR surprise. After controlling for the firm, analyst, broker characteristics and macroeconomic factors, as well as firm and year fixed effects, the results show that the coefficients on *Abs_Surprise* are positive and significant (coef=4.88; t-stat=2.64). This result suggests that the FFR surprises increase analysts' forecast errors, leading to a deterioration in their performance. In economic terms, a 1% increase in FFR surprise leads to a 4.88% increase in analysts' proportional mean absolute forecast error.

Next, the signed forecast errors are used and the signed FFR surprises are split into positive (i.e., expansionary) and negative (i.e., contractionary) surprises for columns 2-4.[24] This further exploration shows that the coefficients on *Surprise* are negative across

of total observations, positive surprise and negative surprise are 0.04%, 0.34% and -0.30%, respectively. Similar to the *Surprise*, the actual changes in target FFR are multiplied by -1 so a positive (negative) value indicates an expansionary (contractionary) monetary policy.

[24] Additionally, the regression model controls for the latest earnings surprise. Though the sample size is

these 3 columns, but they are statistically significant in the total values of surprise and positive surprise samples (coef=-0.115; t-stat=-2.22; coef=-0.337; t-stat=-3.87). These results are consistent with H1b that the monetary policy surprises bias analysts' short-term earnings forecasts and suggest that biased earnings forecasts are due to forecast earnings being higher (lower) than actual earnings when analysts view FFR surprises as good news (bad news) for firms.

As compared to contractionary monetary policy surprises, analysts are more sensitive to expansionary monetary surprises. This finding is consistent with previous studies. For instance, Gallo et al. (2016) find that the stock market reacts significantly to expansionary monetary policy surprises, but not to contractionary ones. Armstrong et al. (2019) find that the moderating effects of firm accounting quality are only significant for expansionary monetary policy surprises.

Alternatively, in the untabulated analysis, the regressions are re-estimated by aggregating the observations to examine the overall U.S. analysts' response to the Fed's monetary policy surprises. The results from these aggregated-level regressions still indicate that analysts have biased forecasts due to the FFR surprises. This aggregation helps us to address the concern about possible bias from the micro-level (e.g., analyst, brokerage house, etc.) to some extent.

So far, the main regression results tend to show the biased forecasts caused by the Fed's monetary policy surprises. However, given the close connection between the monetary policy and macroeconomic factors, there is some concern about possible endogeneity emanating from the construction of this policy surprise, namely that the surprise variable might not only capture the unexpected expectation about monetary policy but might also reflect macroeconomic uncertainty. This macroeconomic uncertainty can also influence analysts' forecasts and might bias the regression estimation. To alleviate this concern, when constructing this surprise variable, this chapter has used a narrow window, which is the daily change of future contract price, around the FOMC meeting date. Furthermore, the regression model has controlled for lagged GDP and

much smaller than that used in Table 2.3, the results from this untabulated analysis are consistent with the conclusions from Table 2.3.

inflation rate, which capture factors related to macroeconomic uncertainty to some extent.

[Insert Table 2.3]

2.5.3: FFR surprise types

The FFR surprises from different FOMC meetings are not homogenous. Previous studies have found that the impacts of monetary policy surprises are affected by the types of FFR surprises, which are linked to different characteristics and occur in different contexts (e.g., Bernanke and Kuttner, 2005, Lakdawala and Schaffer, 2019). This section examines whether analysts' biased forecasts vary across different types of FFR surprise. First, FFR surprises differ in terms of their impact on market expectations of future interest rates. While some FFR surprises are viewed by the market as changing the expected path of the FFR in the next few months (i.e., level surprises), others are regarded as purely timing differences in having information on current monetary policy (i.e., timing surprises). Compared with the timing surprises, level surprises will have a greater impact on analysts. Following Bernanke and Kuttner (2005), the timing surprise is measured as the difference between the change in the 3-month-ahead futures rate and the current FFR surprise (*Timing surprise*). Adding the variable of the *Timing surprise* to Eq. (2.1), the original variable of the *Surprise* in the regression model will now capture the level surprises:

$$\begin{aligned} FE = \ & \beta_0 + \beta_1 \cdot Surprise + \beta_2 \cdot Timing\ surprise + Analyst\ Controls \\ & + Broker\ Controls + Firm\ Controls + Macro\ Controls + \gamma_t + \theta_j \\ & + \varepsilon_0 \qquad (2.2) \end{aligned}$$

Timing surprise is the difference between the change in the 3-month-ahead futures rate and the current FFR surprise. Following Eq. (2.1), this regression model includes the same control variables and the same set of fixed effects. The regression model is estimated by using OLS regression and standard errors are clustered by firm.

As shown in Table 2.4 columns 1 and 2, the coefficients on *Surprise* are negative and significant, while the coefficients on *Timing surprise* are insignificant. These results indicate that the analysts' biased forecasts are mainly driven by the level surprise, suggesting that analysts have a strong response to monetary policy actions that have a persistent impact on the economy.

[Insert Table 2.4]

Second, the FFR surprises differ in the direction of actual FFR changes. Specifically, there are 8 FOMC meetings that reverse the direction of the actual FFR changes compared with the previous meetings (i.e., from a decreasing target FFR in one meeting to an increasing target FFR in the next meeting or vice versa). These turning-point FOMC meetings are likely to make market participants revise their expectations of the future policy path. Therefore, these FFR surprises from turning-point FOMC meetings will have greater impacts on analysts than "typical" FOMC meetings. Empirically, the following regression model is employed:

$$FE = \beta_0 + \beta_1 \cdot Surprise + \beta_2 \cdot Reverse\ direction + \beta_3 \cdot Surprise \cdot Reverse\ direction + Analyst\ Controls + Broker\ Controls + Firm\ Controls + Macro\ Controls + \gamma_t + \theta_j + \varepsilon_0 \quad (2.3)$$

Reverse direction is a dummy variable that equals to 1 if the target FFR in the current FOMC meeting reverses the direction of the previous ones, and 0 otherwise. Following Eq. (2.1), this regression model includes the same control variables and the same set of fixed effects. The regression model is estimated by using OLS regression and standard errors are clustered by firm.

Table 2.5 columns 1 and 2 show that the interaction term between the dummy variable of the turning-point FOMC meetings (*Reverse direction*) and *Surprise* are negative and significant, suggesting that these meetings drive analysts' biased forecasts. Alternatively, in an untabulated analysis, 20 FOMC meetings are found in which the FFR surprises changed from 0 to positive and 9 FOMC meetings in which the FFR surprises changed from 0 to negative. By defining these 29 meetings as the turning point, qualitatively similar results are still obtained.

[Insert Table 2.5]

Third, the FFR surprises differ in terms of whether the FOMC discloses meeting schedules to the public in advance. While the FOMC normally hosts 8 scheduled meetings per year and information on these meeting schedules is publicly available in advance, it may also host unscheduled meetings, of which the public are not informed until they are finished. These unscheduled meetings are necessary responses to the urgent call of economic and financial conditions, and thus, analysts should have a larger response to unscheduled meetings. There are 23 unscheduled meetings in the sample.[25] To examine this prediction, the following regression model is used:

$$FE = \beta_0 + \beta_1 \cdot Surprise + \beta_2 \cdot Unscheduled + \beta_3 \cdot Surprise \cdot Unscheduled + Analyst\ Controls + Broker\ Controls + Firm\ Controls + +Macro\ Controls + \gamma_t + \theta_j + \varepsilon_0 \quad (2.4)$$

Unscheduled is a dummy variable that equals to 1 if an FOMC meeting is unscheduled, and 0 otherwise. Following Eq. (2.1), this regression model includes the same control variables and the same set of fixed effects. The regression model is estimated by using OLS regression and standard errors are clustered by firm.

As shown in Table 2.6 columns 1 and 2, the coefficients on the interaction term between the dummy variable of the unscheduled meetings (*Unscheduled*) and *Surprise* are negative and significant, indicating that analysts' biased forecasts are mainly driven by these unscheduled meetings. These findings are consistent with previous studies that the FFR surprises from unscheduled FOMC meetings have a greater impact on the financial market than scheduled ones (e.g., Lakdawala and Schaffer, 2019).

[Insert Table 2.6]

2.5.4: The Fed's communication strategies

The Fed has significantly improved its communication strategies in the past decades, especially its FOMC post-meeting disclosure. Table 2.7 shows the changes in FOMC post-meeting disclosure. While the Fed tended to keep quiet in the past, it has implemented a variety of methods to improve its communication (Blinder et al., 2008). This section examines analysts' biased forecasts due to FFR surprises, conditional on the FOMC post-meeting disclosure strategies. First, since February 1994, the FOMC has significantly improved communication by releasing a post-meeting statement to disclose the target FFR immediately. This improvement in its communication with the public was

[25] Excluding the unscheduled meeting held on 17th Sept 2001 as described in the sample selection.

a milestone for the Fed. To investigate analysts' forecasts in the pre and post-1994 periods, the following regression model is employed:

$$FE = \beta_0 + \beta_1 \cdot Surprise + \beta_2 \cdot Surprise \cdot Past\_1994 + Analyst\ Controls + Broker\ Controls + Firm\ Controls + Macro\ Controls + \gamma_t + \theta_j + \varepsilon_0 \quad (2.5)$$

Post_1994 is a dummy variable that equals to 1 if FOMC meetings are after February 1994, and 0 otherwise. Following Eq. (2.1), this regression model includes the same control variables and the same set of fixed effects. The variable of *Post_1994* itself has been omitted from the regression model because it is fully absorbed by year fixed effects. The regression model is estimated by using OLS regression and standard errors are clustered by firm.

In Table 2.8, columns 1, 3 and 5 give the results for the total sample, and the positive and negative surprise samples respectively. The results appear to show that the analysts' biased forecasts can be traced to the post-1994 period for the positive surprise. The coefficient on *Surprise* itself is insignificant; that on the surprise interacted with the *post_1994* dummy is significant. These results indicate that releasing the target FFR through the post-meeting statement might not be an efficient communication strategy with the market in the sense that it makes analysts produce biased forecasts. The above finding is also consistent with previous studies that improved central bank information disclosure might be detrimental to the markets (e.g., Morris and Shin, 2002, Ehrmann and Fratzscher, 2009).

Second, since FOMC started to disclose target FFR immediately after meetings in 1994, greater efforts were made to further improve FOMC post-meeting disclosure during 1997 and 2002. As shown in Table 2.7, these further improvements include explicitly aligning monetary policy with the target FFR, providing information on the future direction of monetary policy, further improving the disclosure of the economic outlook as well as the balance of the risk, and providing information on the votes of FOMC members. To capture these 4 improvements in FOMC post-meeting disclosure, a factor variable with value ranging from 0 to 4 (*post_1994_change*) is created. A higher value of the *post_1994_change* indicates better post-meeting disclosure. To examine the impact of these further improvements in FOMC post-meeting disclosure, the sample includes observations obtained since 1994, and the following regression model is employed:

$$FE = \beta_0 + \beta_1 \cdot Surprise + \beta_2 \cdot Past\_1994\_change + \beta_3 \cdot Surprise \cdot Past\_1994\_change + Analyst\ Controls + Broker\ Controls + Firm\ Controls + Macro\ Controls + \gamma_t + \theta_j + \varepsilon_0 \quad (2.6)$$

$Post\_1994\_change$ is a factor variable that measures the improvements in FOMC post-meeting disclosure. Its value ranges from 0 to 4, and a higher value indicates better post-meeting disclosure. Following Eq. (2.1), this regression model includes the same control variables and the same set of fixed effects. The regression model is estimated by using OLS regression and standard errors are clustered by firm.

The results in Table 2.8 column 4 show that, while the coefficients on *Surprise* are negative and significant, the coefficients on the interaction term between *Surprise* and *post_1994_change* are insignificant. These results suggest that further enhanced post-meeting disclosure still cannot alleviate analysts' biased forecasts caused by the disclosure of target FFR.

[Insert Table 2.7 and 2.8]

2.5.5: Firms' reporting qualities

This section examines the role of firms' reporting qualities in the relationship between analysts' earnings forecasts and FFR surprises. Firms' accounting information is crucial to analysts' forecasts. The literature has well documented the positive association between the quality of firms' earnings information and analysts' forecast performance (e.g., Hope, 2003, Chen et al., 2015a). Analysts need high-quality past earnings information to assess how firms' performance is influenced by economic shocks. However, poor reporting quality, such as earnings management, could mask the true underlying activities and performances of firms, which makes it more difficult for analysts to assess the impact of monetary policy surprises on firms and leads to biased forecasts.

Given the importance of earnings information in analysts' forecasts, firms' reporting qualities are measured by the accruals. Specifically, following previous studies (e.g., Irani and Oesch, 2016), absolute discretionary accruals are calculated on the basis of the modified Jones model (Dechow et al., 1995), and absolute current accruals on the basis of Sloan (1996) and Hribar and Collins (2002).

Table 2.9 presents the regressions in Table 2.3 column 2 by using the sub-samples with large or low values of reporting quality measurements. The results show that coefficients on *Surprise* in the sub-samples with large absolute discretionary accruals or large absolute current accruals are significant. These results are consistent with the prediction that poor reporting quality makes it difficult for analysts to assess the impact of monetary policy on firms' performance, leading to biased forecasts.

[Insert Table 2.9]

2.6. Conclusion

This chapter examines the impact of the central bank's monetary policy surprise on the financial analysts' short-term earnings forecasts. Relying on the FOMC meetings, the empirical results show that the Fed's monetary policy surprises bias analysts' forecasts and these biased forecasts are mainly driven by unexpected expansionary surprises. This chapter further investigates analysts' biased forecasts across different types of FFR surprises, and finds that FFR surprises with persistent impacts on economies, from the FOMC meetings that reverse the direction of FFR changes, and occurred during the unscheduled FOMC meetings drive the results of biased forecasts.

Next, this chapter examines the impacts of the Fed's communication strategies on the analysts' biased forecasts. This chapter finds that, though the Fed has tried to improve its communication with the public by disclosing target FFR in the FOMC post-meeting statement, it is still not ideal in the sense that it causes analysts to produce biased forecasts. Additionally, the further improvements in post-meeting disclosure made between 1997 and 2002 still cannot alleviate these biased forecasts.

Finally, this chapter examines the role of the firms' reporting quality in the association between analysts' earnings forecasts and FFR surprises. By splitting the samples on the basis of absolute discretionary accruals or absolute current accruals, this chapter finds that firms with poor reporting quality drive the results of biased forecasts.

In general, the empirical findings of Chapter 2 show the impacts of the central bank's monetary policy, but they have limitations to some extent. First, the findings of biased earnings forecasts provide some preliminary results suggesting that the analysts might be irrational in processing the central bank’s monetary policy surprise. However, the earnings forecasts are at the aggregate level, and the detailed components of earnings that worsen the analysts’ forecasts and account for biased forecasts require further exploration. Second, though the empirical analysis has taken measures to alleviate the concern that monetary policy surprise captures macroeconomic uncertainty, it might not be sufficient to some extent. Further measures to control for unexpected macroeconomic information could be implemented in the future. Third, the findings are based on the research setting of FOMC open market operation and thus might not be generalizable to the periods when the Fed implemented unconventional monetary policy, which is one of the areas that attract attention from both academia and practitioners.

Collectively, the above evidence indicates that monetary policy surprise has a significant impact on the analysts’ short-term earnings forecasts. The findings of this chapter have policy implications for the central bankers and other regulators in terms of central bank communication and expectation management.

Appendix 2.1. Construction of the monetary policy surprises

This method first calculates the change in the rate implied by the corresponding federal funds futures contract, given by 100 minus the futures contract price. This result is then scaled by a factor associated with the number of days of the month in which the event occurred because the payoff of the contract is determined by the average realized federal funds effective rate during the month. Accordingly, the monetary policy surprise, which is the unexpected target rate change for an event taking place on the FOMC announcement meeting date on day d of month m is given by:

$$\Delta i^u = \frac{D}{D-d}\left(f_{m,d}^0 - f_{m,d-1}^0\right)$$

Where $f_{m,d}^0$ is the implied futures rate calculated as 100 minus the contract price of current-month federal funds futures, $f_{m,d}^0 - f_{m,d-1}^0$ is the change in the current-month implied futures rate, and D is the number of days in the month. To suppress the end-of-month noise in the federal funds rate, the unscaled change in the 1-month futures rate is used as the measure of the target rate surprise when the event occurs during the last three days of a month. If the event happens on the first day of the month, the 1-month futures rate from the final day of the last month (i.e., $f_{m-1,D}^1$) is used instead of $f_{m,d-1}^0$ in the calculation. [26] To assist the interpretation, the above calculated surprise is multiplied by -1 to construct the variable of the Fed's monetary policy surprise.

$$Surprise = -\Delta i^u = -\frac{D}{D-d}\left(f_{m,d}^0 - f_{m,d-1}^0\right)$$

[26] The resultant data for these policy surprises are publicly available from Kenneth Kuttner's web page (http://econ.williams.edu/profile/knk1/).

Appendix 2.2. Variable Definitions

Variable	Definition	Data source
<u>Dependent variables</u>		
FE	Actual earnings per share (EPS) minus the analyst’s earnings forecast, scaled by the price at the beginning of the quarter.	I/B/E/S and CRSP
Proportional absolute mean FE	Difference between absolute forecast error for an analyst's forecast of a firm and mean absolute forecast error for a firm, scaled by mean absolute forecast error for a firm.	I/B/E/S and CRSP
<u>Test variables</u>		
Surprise	The Fed's policy surprise is measured as the daily change in the Fed’s funds rate futures contracts between the FOMC announcements date and the previous trading day, and this calculated policy surprise is multiplied by -1.	Datastream
Abs_Surprise	Absolute value of the Fed's policy surprise.	Datastream
Timing surprise	Difference between the change in the 3-month-ahead futures rate and the current Fed's policy surprise.	Datastream
Reverse direction	A dummy variable equals to 1 for observations that target funds rate from the most recent FOMC reverses the direction of the previous ones, 0 otherwise.	Fed
Unscheduled	A dummy variable equals to 1 for observations when the FOMC meetings are unscheduled, 0 otherwise.	Fed
Post_1994	A dummy variable equals to 1 for observations when FOMC meetings after 1994, 0 otherwise.	Fed

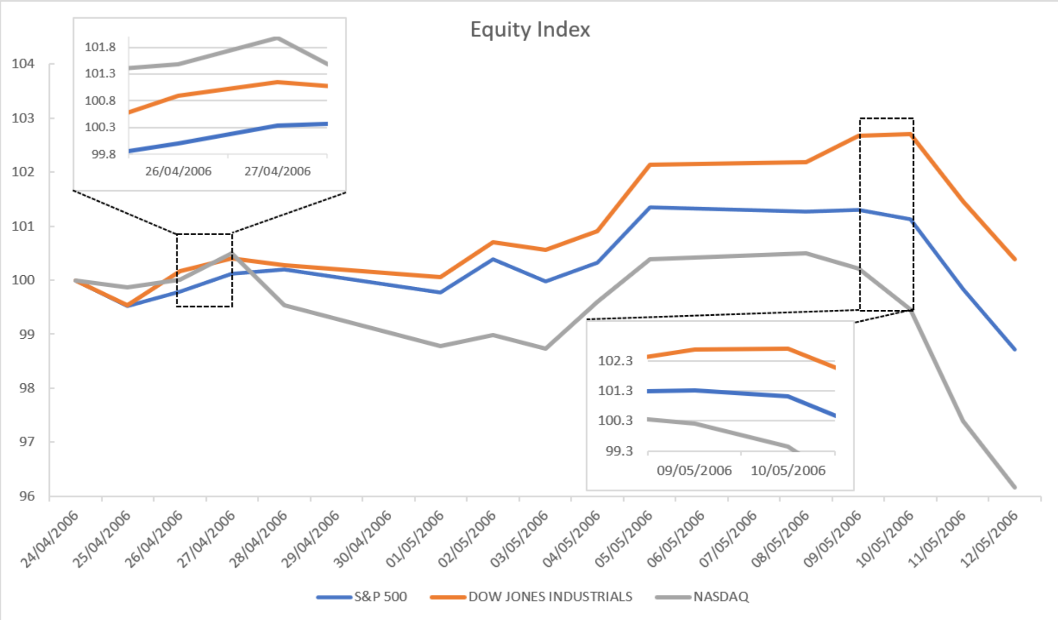
Appendix 2.2. Variable Definitions (continued)

Variable	Definition	Data source
Test variable		
Post_1994_change	A factor variable that measures the changes in FOMC post-meeting disclosure. It ranges from 0 to 4, and higher values indicate better disclosure. It is equal to 0 for FOMC meetings beginning from February 1994 and before August 1997; equals to 1 for meetings beginning from August 1997 and before May 1999; equals to 2 for meetings beginning from May 1999 and before February 2000; equals to 3 for meetings beginning from February 2000 and before March 2002; equals to 4 for meetings beginning from March 2002.	Fed
Control variables		
NFIRM	Number of firms that the analyst follows during the quarter.	I/B/E/S
NIND	Number of Fama-French 48 industries that the analyst follows during the quarter.	Compustat
HORIZON	Number of days between the analyst's earnings forecast date and the firm's announcement date for the quarter.	I/B/E/S
FEXP	Number of quarters for which the analyst has issued at least one earnings forecast for the firm prior to the quarter.	I/B/E/S
BSIZE	Number of unique analysts employed by an analyst's brokerage house during the quarter.	I/B/E/S
LAG_TACC	Firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter.	Compustat
LAG_PROFIT	Firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter.	Compustat
LAG_SIZE	Natural logarithm of the market value of equity in the prior quarter.	Compustat

Appendix 2.2. Variable Definitions (continued)

Variable	Definition	Data source
Test variable		
LAG_INFLATION	U.S. 12-month inflation rate in the prior month.	Bureau of Labour Statistics
LAG_GDP	Natural logarithms of U.S. GDP in billions of USD in the prior quarter.	St. Louis Fed
Partition variables		
Abs DAC based on the modified Jones model	Absolute value of a firm's discretionary accruals based on the modified Jones model. Discretionary accruals are the residual from the regression of a firm's total accruals (i.e., the difference between net income and cash flow from operations, scaled by lagged total assets) on reciprocal of lagged total assets, changes in revenues (i.e., difference in sale revenues, scaled by lagged total assets) and PPE (i.e., gross property, plant and equipment, scaled by lagged total assets). The regression is estimated at industry-year level.	Compustat
Abs Sloan CA	Absolute value of a firm's current accruals, calculated as the change in current assets minus the change in current liabilities, minus the change in cash holdings, and minus depreciation and amortization expense, scaled by lagged total assets.	Compustat
Abs Hribar & Collins CA	Absolute value of a firm's current accruals, calculated as earnings before extraordinary items and discontinued operations minus operating cash flows from continuing operations, scaled by lagged total assets.	Compustat

Figure 2.1. Market reaction to monetary policy



Dow Rise on Bernanke Testimony

By **Jerry Knight**
April 27, 2006

Stocks edged higher today after Wall Street interpreted comments by Federal Reserve Chairman Ben S. Bernanke to mean that the Fed may soon take a break from its steady series of interest rate increases.

Whether Bernanke was promising a pause -- or merely saying it is possible -- was debatable, but interest rates fell and stocks rose in response to his congressional testimony.

The Dow Jones industrial average gained 28 points to close at 11,382.51; the Nasdaq Stock Market composite index rose 11 points to 2,344.95; and Standard & Poor's 500 stock index advanced 4 points to 1,309.72.

The Fed chairman also said the economy "has been performing well and the near-term prospects look good," but he predicted "a gradual cooling" in the months ahead.

One factor that could slow economic growth is the high cost of energy, which is becoming as much of a worry for Washington lawmakers as it is to Wall Street investors.

Figure 2.2. EVERCORE ISI's report on Ford Motor

May 05, 2022

EvrISI Autos Pitstop: Autos & the Fed / FSR Ronin / BWA & UBER rehash / Clean Energy Summit Signups!!!

- **Fed goes 50…but short-term rates are a side-story in Autos** – while rates will always be wrapped in any "consumer recession" debate, the reality is that Autos have typically worked in a slow rising front-end rate environment and rates (both 10yr & Auto lending) are low by historical standards (flat the last 5 years). Many investors would also be surprised that a ~100bp move in rates may only move the average $600+ monthly payment by ~$15. **EvrISI Take** – we are not blind to the impact of the Fed on the broader market sentiment & perception of US recession…our main point (as laid out in "Binary Bullish" Q1 Outlook) is that ***what matters more…is "conflict resolution***" leading to 2H/'23 production visibility (as well as second-order clarity on raw materials). ***We are willing to fight the Fed…just not world wars for Autos.***

Figure 2.3. Theoretical framework

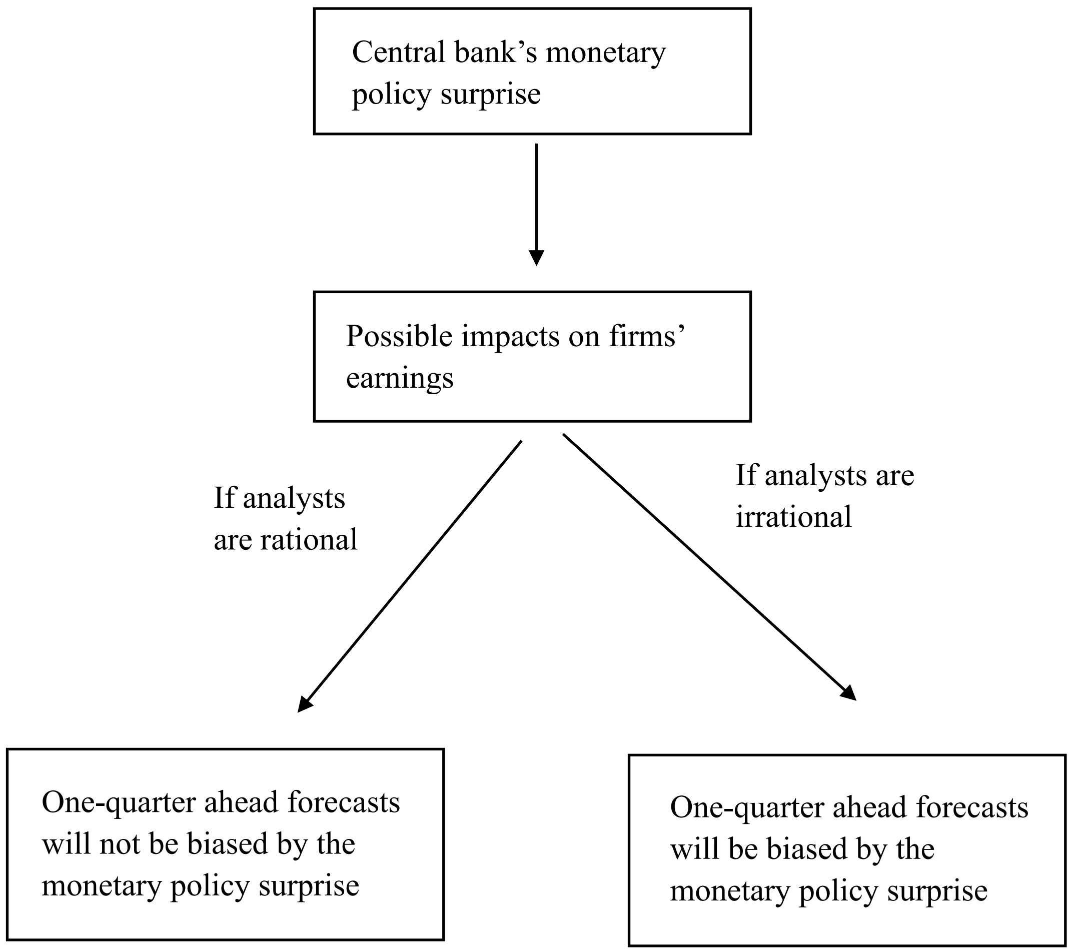


Figure 2.4. Timeline of analysts' forecasts

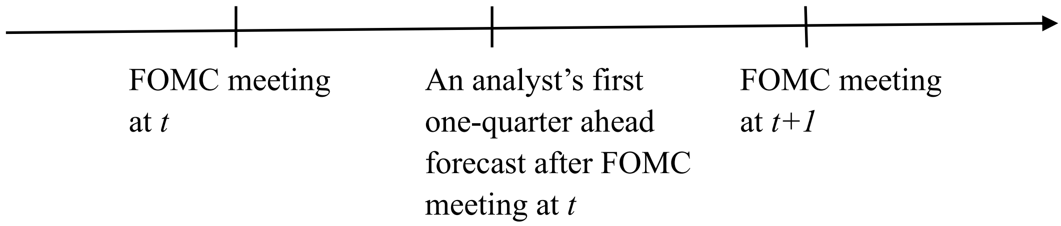


Table 2.1. Sample selection

Initial sample: I/B/E/S initial one-quarter-ahead earnings forecasts, 1989-2008	1,739,206
Remaining	
Retain: earnings forecasts issued in USD, identified analysts, and non-missing estimated value and actual value	1,723,553
Retain: first earnings forecast issued after the current FOMC meeting	1,486,248
Retain: earnings forecasts with non-missing CRSP price to deflate the and SIC	1,445,220
Retain: earnings forecasts with available data to compute the control variables	1,292,739
Retain: non-financial institutions and non-utilities	1,123,188
Retain: earnings forecasts issued before actual earnings announcement dates	1,004,953
Table 2.3	231,026-1,004,953
Table 2.4	231,026-1,004,953
Table 2.5	231,026-1,004,953
Table 2.6	231,026-1,004,953
Table 2.8	202,009-1,004,953
Table 2.9	367,483-481,379

This table presents the sample selection for the analyses in Tables 2.3, 2.4, 2.5, 2.6, 2.8, 2.9. The sample period is 1989 to 2008.

Table 2.2. Descriptive statistics

Panel A: Monetary policy shock

	#Obs	Mean	SD	Min	P25	P50	P75	Max
Surprise (%)	176	0.0313	0.1056	-0.1700	-0.0100	0.0000	0.0400	0.7400
Positive_Surprise (%)	77	0.1022	0.1208	0.0100	0.0300	0.0500	0.1500	0.7400
Negative_Surprise (%)	45	-0.0527	0.0437	-0.1700	-0.0600	-0.0400	-0.0200	-0.0100

Panel B: Other key variables

	Total Policy Surprise			Positive Policy Surprise (Expansionary)			Negative Policy Surprise (Contractionary)		
	#Obs	Mean	Median	#Obs	Mean	Median	#Obs	Mean	Median
PAMFE	823,860	5.5342	-5.8824	316,335	6.7899	-5.2674	189,254	3.7451	-7.0422
FE	1,004,953	-0.1730	0.0090	395,973	-0.2005	0.0033	231,026	-0.1554	0.0085
NFIRM	1,004,953	11.6290	11.0000	395,973	11.6500	11.0000	231,026	11.6610	11.0000
NIND	1,004,953	5.0961	4.0000	395,973	5.3130	5.0000	231,026	5.1310	4.0000
FEXP	1,004,953	7.6261	5.0000	395,973	7.5492	5.0000	231,026	7.6435	5.0000
HORIZON	1,004,953	61.9690	69.0000	395,973	62.5330	70.0000	231,026	59.9480	63.0000
BSIZE	1,004,953	42.9100	35.0000	395,973	42.8610	35.0000	231,026	42.7680	33.0000
LAG_TACC	1,004,953	-0.0394	-0.0334	395,973	-0.0359	-0.0303	231,026	-0.0391	-0.0335
LAG_PROFIT	1,004,953	0.0090	0.0138	395,973	0.0089	0.0138	231,026	0.0084	0.0133

LAG_SIZE	1,004,953	21.1700	21.0810	395,973	21.0690	20.9840	231,026	21.1280	21.0420
LAG_INFLATION	1,004,953	0.0285	0.0280	395,973	0.0294	0.0290	231,026	0.0290	0.0280
LAG_GDP	1,004,953	9.1915	9.2530	395,973	9.1187	9.1183	231,026	9.1673	9.2530

The table reports descriptive statistics. Panel A provides the descriptive statistics for the Fed's monetary policy surprise during the period 1989 to 2008 with the exception of 17th September, 2001. *Surprise* is a daily change in the Fed's funds rate futures contracts between the FOMC announcement date and the previous trading day, and this calculated policy surprise is multiplied by -1. This figure is expressed as a percentage. *Positive Surprise* includes the observations with values of *Surprise* larger than 0. *Negative Surprise* includes the observations with values of *Surprise* lower than 0. Panel B provides descriptive statistics for variables used in the tests. *PAMFE* is the proportional absolute mean forecast error, defined as the difference between absolute forecast error for an analyst forecast of a firm and mean absolute forecast error for a firm, scaled by mean absolute forecast error for a firm. This figure is multiplied by 100 to express it as a percentage. *FE* is analyst forecast error, defined as actual earnings per share minus the analyst earnings forecast, scaled by the price at the beginning of the quarter. This figure is multiplied by 100 to express it as a percentage. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *HORIZON* is the number of days between an analyst's earnings forecast date and the firm's earnings announcement date. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 2.2.

Table 2.3 Analysts' forecasts to monetary policy surprises

	Abs FE	Signed FE		
	Proportional absolute mean FE	Total Policy Surprise	Positive Policy Surprise (Expansionary)	Negative Policy Surprise (Contractionary)
	(1)	(2)	(3)	(4)
Abs_Surprise	4.8844***			
	(2.64)			
Surprise		-0.1149**	-0.3374***	-0.2626
		(-2.22)	(-3.87)	(-0.91)
NFIRM	0.0595**	-0.0013	0.0004	-0.0017
	(2.10)	(-1.63)	(0.34)	(-1.33)
NIND	0.3302***	0.0002	-0.0040*	0.0008
	(5.15)	(0.10)	(-1.88)	(0.31)
BSIZE	-0.0376***	0.0003***	0.0004***	0.0005***
	(-8.62)	(4.69)	(3.66)	(3.91)
HORIZON	0.5335***	-0.0033***	-0.0036***	-0.0026***
	(57.33)	(-22.31)	(-17.61)	(-8.83)
FEXP	-0.1228***	0.0004	0.0006	-0.0005
	(-9.00)	(1.54)	(1.37)	(-1.03)
LAG_TACC	-8.4460***	-0.2131**	-0.2893**	-0.4201**
	(-8.93)	(-1.98)	(-1.98)	(-2.08)
LAG_PROFIT	6.2401***	1.6171***	1.4617***	1.7946***
	(2.69)	(4.61)	(2.89)	(2.97)
LAG_SIZE	-0.6064***	0.0982***	0.1320***	0.0179
	(-4.73)	(5.80)	(6.20)	(0.70)
LAG_INFLATION	62.7212***	-2.6058**	-5.4956***	-3.2105

	(3.40)	(-2.36)	(-3.13)	(-1.14)
LAG_GDP	-106.1850***	-1.6255***	-0.0561	-3.2716***
	(-14.15)	(-5.40)	(-0.12)	(-3.48)
Intercept	903.6240***	12.1852***	-1.8832	28.0059***
	(14.00)	(4.80)	(-0.45)	(3.49)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	823,860	1,004,953	395,973	231,026
Adj. R-square	3.1%	17.3%	21.8%	24.1%

This table presents the regression analysis of the forecast error on the Fed's monetary policy surprise. The dependent variable in the column *Abs FE* is the proportional mean absolute forecast error (*PMAFE*), defined as the difference between the absolute forecast error for an analyst forecast of a firm and the mean absolute forecast error for a firm, scaled by mean absolute forecast error for a firm. This figure is multiplied by 100 to express it as a percentage. The dependent variable in the *Signed FE* column is analyst forecast error, defined as actual earnings per share minus the analyst earnings forecast, scaled by the price at the beginning of the quarter. This figure is multiplied by 100 to express it as a percentage. The *Abs FE* and *Total Policy Surprise* columns under *Signed FE* include observations with all values of *Surprise*. The *Positive Policy Surprise* column under *Signed FE* includes the observations with values of *Surprise* larger than 0. The *Negative Policy Surprise* column under *Signed FE* includes the observations with values of *Surprise* lower than 0. *Surprise* is a daily change in Fed's funds rate futures contracts between the FOMC announcement date and the previous trading day, and this calculated policy surprise is multiplied by -1. This figure is expressed as a percentage. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and the firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 2.2. The *t*-

statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Table 2.4 Level surprise vs timing surprise

	Total Policy Surprise (1)	Positive Policy Surprise (Expansionary) (2)	Negative Policy Surprise (Contractionary) (3)
Surprise	-0.1370**	-0.3314***	-0.2710
	(-2.31)	(-3.60)	(-0.94)
Timing surprise	-0.0663	0.0231	-0.0458
	(-1.32)	(0.33)	(-0.30)
NFIRM	-0.0013	0.0004	-0.0017
	(-1.63)	(0.34)	(-1.33)
NIND	0.0002	-0.0040*	0.0008
	(0.11)	(-1.88)	(0.32)
BSIZE	0.0003***	0.0004***	0.0005***
	(4.69)	(3.66)	(3.91)
HORIZON	-0.0033***	-0.0036***	-0.0026***
	(-22.29)	(-17.58)	(-8.70)
FEXP	0.0004	0.0006	-0.0005
	(1.54)	(1.38)	(-1.03)
LAG_TACC	-0.2127**	-0.2892**	-0.4215**
	(-1.97)	(-1.98)	(-2.09)
LAG_PROFIT	1.6183***	1.4612***	1.7978***
	(4.61)	(2.89)	(2.97)
LAG_SIZE	0.0981***	0.1320***	0.0179
	(5.80)	(6.20)	(0.70)
LAG_INFLATION	-2.6516**	-5.4245***	-3.1323
	(-2.40)	(-3.11)	(-1.11)
LAG_GDP	-1.6168***	-0.0440	-3.1444***
	(-5.37)	(-0.09)	(-2.95)
Intercept	12.1101***	-1.9901	26.9031***
	(4.77)	(-0.48)	(2.95)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,004,953	395,973	231,026
Adj. R-square	17.3%	21.8%	24.1%

This table presents a regression analysis of the forecast error on the Fed's monetary policy surprise, conditional on the level or timing surprise. The *Total Policy Surprise* column includes observations with all values of *Surprise*. The *Positive Policy Surprise* column includes observations with values of *Surprise* larger than 0. The *Negative Policy Surprise* column includes observations with values of *Surprise* lower than 0. The dependent variable is analyst forecast error, defined as actual earnings per share minus the analyst earnings forecast, scaled by the price at the beginning of the quarter. This figure is multiplied by 100 to express it as a percentage. *Surprise* is a daily change in the Fed's funds rate futures contracts between the FOMC announcement date and the previous trading day, and this calculated policy surprise is multiplied by -1. This figure is expressed as a percentage. *Timing surprise* is the difference between the change in the 3-month-ahead futures rate and the current FFR surprise. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and the firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 2.2. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Table 2.5 FOMC meetings with reverse direction in monetary policy

	Total Policy Surprise	Positive Policy Surprise (Expansionary)	Negative Policy Surprise (Contractionary)
	(1)	(2)	(3)
Surprise	-0.0166	-0.1874**	-0.2647
	(-0.35)	(-2.34)	(-0.90)
Surprise*Reverse direction	-0.6942***	-1.0758***	2.2059*
	(-3.85)	(-4.20)	(1.75)
Reverse direction	-0.0098	0.0427	0.1690
	(-0.67)	(1.53)	(1.35)
NFIRM	-0.0013*	0.0002	-0.0017
	(-1.66)	(0.24)	(-1.32)
NIND	0.0002	-0.0039*	0.0007
	(0.14)	(-1.84)	(0.29)
BSIZE	0.0003***	0.0004***	0.0005***
	(4.70)	(3.68)	(3.89)
HORIZON	-0.0033***	-0.0037***	-0.0026***
	(-22.42)	(-18.02)	(-8.80)
FEXP	0.0004	0.0006	-0.0005
	(1.56)	(1.46)	(-1.01)
LAG_TACC	-0.2087*	-0.2974**	-0.4316**
	(-1.93)	(-2.03)	(-2.13)
LAG_PROFIT	1.6281***	1.4992***	1.7978***
	(4.64)	(2.96)	(2.98)
LAG_SIZE	0.0994***	0.1357***	0.0179
	(5.89)	(6.41)	(0.70)
LAG_INFLATION	-2.5129**	-5.1249***	-3.1920
	(-2.26)	(-2.94)	(-1.13)
LAG_GDP	-1.6491***	-0.5325	-3.9194***
	(-5.36)	(-1.11)	(-3.63)
Intercept	12.3549***	2.1287	33.6066***
	(4.76)	(0.51)	(3.64)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,004,953	395,973	231,026
Adj. R-square	17.3%	21.8%	24.1%

This table presents a regression analysis of the forecast error on the Fed's monetary policy surprise, conditional on whether the FOMC meetings incur reversing direction in actual monetary policy. The *Total Policy Surprise* column includes observations with all values of *Surprise*. The *Positive Policy Surprise* column includes the observations with values of *Surprise* larger than 0. The *Negative Policy Surprise* column includes the observations with values of *Surprise* lower than 0. The dependent variable is analyst forecast error, defined as actual earnings per share minus the analyst earnings forecast, scaled by the price at the beginning of the quarter. This figure is multiplied by 100 to express it as a percentage. *Surprise* is a daily change in Fed's funds rate futures contracts between the FOMC announcement date and the previous trading day, and this calculated policy surprise is multiplied by -1. This figure is expressed as a percentage. *Reverse direction* is a dummy variable that equals to 1 if the FOMC target funds rate reverses the direction of previous ones, and 0 otherwise. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and the firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 2.2. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Table 2.6 Scheduled vs Unscheduled FOMC meetings

	Total observations (1)	Positive Policy Surprise (Expansionary) (2)	Negative Policy Surprise (Contractionary) (3)
Surprise	0.1180**	0.0106	-0.3276
	(2.23)	(0.10)	(-1.11)
Surprise *Unscheduled	-0.4844***	-0.4768***	-0.4718
	(-4.28)	(-2.77)	(-0.16)
Unscheduled	0.0296	0.0358	0.0207
	(1.62)	(0.91)	(0.07)
NFIRM	-0.0013*	0.0003	-0.0017
	(-1.67)	(0.29)	(-1.33)
NIND	0.0002	-0.0040*	0.0008
	(0.13)	(-1.87)	(0.32)
BSIZE	0.0003***	0.0004***	0.0005***
	(4.74)	(3.75)	(3.88)
HORIZON	-0.0033***	-0.0036***	-0.0026***
	(-22.29)	(-17.58)	(-8.86)
FEXP	0.0004	0.0006	-0.0005
	(1.56)	(1.37)	(-1.04)
LAG_TACC	-0.2119**	-0.2908**	-0.4246**
	(-1.96)	(-1.99)	(-2.10)
LAG_PROFIT	1.6227***	1.4642***	1.7945***
	(4.62)	(2.90)	(2.97)
LAG_SIZE	0.0984***	0.1330***	0.0178
	(5.82)	(6.25)	(0.70)
LAG_INFLATION	-2.3532**	-5.6665***	-3.0158
	(-2.15)	(-3.29)	(-1.07)
LAG_GDP	-1.7270***	-0.4695	-3.2159***
	(-5.77)	(-1.02)	(-3.42)
Intercept	13.0307***	1.6469	27.4873***
	(5.16)	(0.41)	(3.42)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,004,953	395,973	231,026
Adj. R-square	17.3%	21.8%	24.1%

This table presents the regression analysis of the forecast error on the Fed's monetary policy surprise, conditional on scheduled or unscheduled FOMC meetings. The *Total Policy Surprise* column includes observations with all values of *Surprise*. The *Positive Policy Surprise* column includes the observations with values of *Surprise* larger than 0.

The *Negative Policy Surprise* column includes the observations with values of *Surprise* lower than 0. The dependent variable is analyst forecast error, defined as actual earnings per share minus the analyst earnings forecast, scaled by the price at the beginning of the quarter. This figure is multiplied by 100 to express it as a percentage. *Surprise* is a daily change in the Fed's funds rate futures contracts between the FOMC announcement date and the previous trading day, and this calculated policy surprise is multiplied by -1. This figure is expressed as a percentage. *Unscheduled* is a dummy variable that equals to 1 for observations when the FOMC meetings are unscheduled, and 0 otherwise. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and the firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 2.2. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Table 2.7 Changes in FOMC post-meeting disclosure

Date	Changes in FOMC post-meeting disclosure
February 1994	FOMC starts to release the post-meeting announcement that discloses the target Federal funds rate.
August 1997	Fed's monetary policy formulation and implementation are explicitly based on the target Federal funds rate.
May 1999	FOMC starts to use the post-meeting announcement to communicate and discuss the future direction of the monetary policy.
February 2000	FOMC improves choices of language in the post-meeting statement to describe the economic outlook and express the view of the committee in terms of the balance of risks.
March 2002	FOMC provides information on the votes of individual FOMC member

This table presents the changes in FOMC post-meeting disclosure between 1989 and 2008.

Table 2.8 Changes in FOMC post-meeting disclosures

	Total observations		Positive Policy Surprise (Expansionary)		Negative Policy Surprise (Contractionary)	
	Whole sample	Sample since 1994	Whole sample	Sample since 1994	Whole sample	Sample since 1994
	(1)	(2)	(3)	(4)	(5)	(6)
Surprise	0.0082	-0.0634	-0.0807	-0.4468***	-0.3071	-0.2551
	(0.11)	(-0.88)	(-0.77)	(-2.80)	(-0.40)	(-0.48)
Surprise * post_1994	-0.1565		-0.3261**		0.0498	
	(-1.55)		(-2.20)		(0.06)	
Surprise*post_1994_change		-0.0350		0.0053		-0.0060
		(-1.29)		(0.10)		(-0.03)
post_1994_change		0.0045		-0.2280***		-0.0122
		(0.19)		(-5.16)		(-0.17)
NFIRM	-0.0013	-0.0016*	0.0003	-0.0005	-0.0017	-0.0014
	(-1.64)	(-1.91)	(0.31)	(-0.40)	(-1.33)	(-1.01)
NIND	0.0002	0.0016	-0.0040*	-0.0009	0.0008	0.0004
	(0.10)	(0.89)	(-1.87)	(-0.37)	(0.32)	(0.13)
BSIZE	0.0003***	0.0003***	0.0004***	0.0004***	0.0005***	0.0005***
	(4.69)	(4.35)	(3.68)	(3.60)	(3.91)	(3.48)
HORIZON	-0.0033***	-0.0031***	-0.0036***	-0.0036***	-0.0026***	-0.0024***
	(-22.32)	(-20.21)	(-17.59)	(-15.97)	(-8.81)	(-7.24)
FEXP	0.0004	0.0004	0.0006	0.0006	-0.0005	-0.0006
	(1.53)	(1.33)	(1.36)	(1.34)	(-1.03)	(-1.02)

LAG_TACC	-0.2139**	-0.1029	-0.2969**	-0.1327	-0.4199**	-0.2535
	(-1.98)	(-0.86)	(-2.02)	(-0.79)	(-2.07)	(-1.13)
LAG_PROFIT	1.6181***	1.2397***	1.4690***	0.9583*	1.7944***	1.4003**
	(4.61)	(3.38)	(2.91)	(1.79)	(2.97)	(2.18)
LAG_SIZE	0.0982***	0.1087***	0.1320***	0.1563***	0.0180	0.0263
	(5.80)	(5.33)	(6.20)	(5.85)	(0.70)	(0.89)
LAG_INFLATION	-2.5788**	-0.7109	-5.6342***	-7.8123***	-3.2050	-2.3490
	(-2.34)	(-0.56)	(-3.19)	(-2.89)	(-1.13)	(-0.77)
LAG_GDP	-1.6202***	-1.7674***	-0.2070	1.8360***	-3.2770***	-3.5659***
	(-5.38)	(-4.80)	(-0.44)	(2.77)	(-3.44)	(-3.78)
Intercept	12.1303***	13.6666***	-0.5958	-19.0800***	28.0506***	31.2364***
	(4.77)	(4.27)	(-0.15)	(-3.27)	(3.45)	(3.77)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,004,953	858,060	395,973	318,876	231,026	202,009
Adj. R-square	17.3%	16.1%	21.8%	20.6%	24.1%	24.0%

This table presents the regression analysis of the forecast error on the Fed's monetary policy surprise, conditional on the changes in the FOMC post-meeting disclosure. The *Total Policy Surprise* column includes observations with all values of *Surprise*. The *Positive Policy Surprise* column includes the observations with values of *Surprise* larger than 0. The *Negative Policy Surprise* column includes the observations with values of *Surprise* lower than 0. The *whole sample* sub-columns include observations obtained between 1989 and 2008. The *sample since 1994* sub-columns include observations obtained between 1994 and 2008. The dependent variable is analyst forecast error, defined as actual earnings per share minus the analyst earnings forecast, scaled by the price at the beginning of the quarter. This figure is multiplied by 100 to express it as a percentage. *Surprise* is a daily change in Fed's funds rate futures contracts between the FOMC announcement date and the previous trading day, and this calculated policy surprise is multiplied by -1. This figure is expressed as a percentage. *Post_1994* is a dummy variable that equals to 1 for FOMC meetings beginning with February 1994, and 0 otherwise. The *Post_1994* itself has been omitted from the regression because it is absorbed by year fixed-effects. *Post_1994_change* is a factor variable that measures the change in FOMC post-meeting disclosure. It ranges from 0 to 4, and higher values indicate better FOMC post-meeting disclosure. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and the firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 2.2. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Table 2.9 Firms' reporting qualities

	Abs DAC based on the modified Jones model	Abs DAC based on the modified Jones model	Abs Hribar & Collins CA	Abs Hribar & Collins CA	Abs Sloan CA	Abs Sloan CA
	Large	Low	Large	Low	Large	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Surprise	-0.2280**	-0.0541	-0.1877**	-0.0156	-0.1749**	-0.0085
	(-2.09)	(-0.96)	(-2.08)	(-0.29)	(-2.22)	(-0.13)
NFIRM	-0.0012	0.0016	-0.0015	-0.0010	0.0002	-0.0001
	(-1.31)	(1.39)	(-1.43)	(-1.23)	(0.17)	(-0.10)
NIND	0.0008	-0.0047**	-0.0002	0.0003	-0.0012	-0.0021
	(0.36)	(-2.33)	(-0.07)	(0.18)	(-0.55)	(-1.26)
BSIZE	0.0004***	0.0003***	0.0005***	0.0002***	0.0003**	0.0003***
	(3.53)	(3.27)	(4.47)	(3.08)	(2.58)	(4.37)
HORIZON	-0.0029***	-0.0032***	-0.0035***	-0.0028***	-0.0035***	-0.0026***
	(-13.11)	(-16.93)	(-16.47)	(-16.37)	(-15.88)	(-15.71)
FEXP	0.0007*	$-2.34*10^{-5}$	0.0007	0.0003	$3.34*10^{-5}$	0.0001
	(1.74)	(-0.06)	(1.59)	(1.00)	(0.08)	(0.42)
LAG_TACC	-0.2062	-0.3220*	-0.1965	0.0564	-0.4431***	-0.0592
	(-1.47)	(-1.71)	(-1.33)	(0.31)	(-3.08)	(-0.40)
LAG_PROFIT	0.6633*	3.4991***	1.2852***	3.4295***	1.2854***	1.4471***
	(1.68)	(4.28)	(3.25)	(4.75)	(2.84)	(2.66)
LAG_SIZE	0.0849***	0.0835***	0.0776***	0.1211***	0.0965***	0.0782***
	(3.61)	(3.05)	(3.09)	(5.89)	(3.68)	(3.39)
LAG_INFLATION	-4.3813***	-0.0368	-3.8777**	-1.9040	-2.9431*	-1.6832

	(-3.03)	(-0.02)	(-2.38)	(-1.43)	(-1.76)	(-1.18)
LAG_GDP	-1.9190***	-1.5200***	-0.7525	-2.1878***	-1.1823**	-1.4534***
	(-4.33)	(-3.58)	(-1.62)	(-5.47)	(-2.41)	(-3.75)
Intercept	15.0582***	11.3089***	5.1708	16.4895***	8.4084**	10.9904***
	(3.98)	(3.13)	(1.30)	(4.96)	(1.98)	(3.42)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	367,486	367,483	481,379	481,379	453,527	453,511
Adj. R-square	22.7%	24.5%	20.2%	22.7%	20.0%	23.8%

This table presents the impacts of the firms' reporting quality. The sample includes observations with all values of *Surprise*. The *Large (Low) Abs DAC based on the modified Jones model* sub-columns include observations with the absolute value of discretionary accruals based on the modified Jones model (Dechow et al. 1995) above (below) the sample median. The *Large (Low) Abs Sloan CA* sub-columns include observations with the absolute value of current accruals based on Sloan (1996) above (below) the sample median. The *Large (Low) Abs Hribar & Collins CA* sub-columns include observations with the absolute value of current accruals based on Hribar and Collins (2002) above (below) the sample median. The dependent variable is analyst forecast error, defined as actual earnings per share minus the analyst earnings forecast, scaled by the price at the beginning of the quarter. This variable is multiplied by 100 to express it as a percentage. *Surprise* is a daily change in Fed's funds rate futures contracts between the FOMC announcement date and the previous trading day, and this calculated policy surprise is multiplied by -1. This figure is expressed as a percentage. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and the firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 2.2. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Chapter 3: Private Information of Central Bank and Financial Analysts[27]

3.1. Introduction

While the monetary policy of the central bank is the focal point for the belief of the market participants, prior studies have documented a series of significant divergences between market expectations and actual policies of the central banks (e.g., Bernanke and Kuttner, 2005). This divergence reflects the fact that central banks might hold private information about macroeconomic conditions (e.g., Melosi, 2017, Romer and Romer, 2000, Frankel and Kartik, 2018, Andrade et al., 2019). Following the disclosure of monetary policy, the market participants can infer the embedded private information. Built on this fact, recent macroeconomic studies uncover the impacts of the central bank's private information on updating market expectations about firms' stock valuation (Nakamura and Steinsson, 2018, Lakdawala and Schaffer, 2019). As important information intermediaries who actively produce equity valuation, the sell-side analysts would infer the private information of the central banks and use it in valuing firms. This chapter examines how the central bank's private information influences analysts' expectations about firms' performance. Based on the Federal Open Market Commission (FOMC) monetary policy meetings, this chapter investigates how the analysts interpret the private information embedded in the Fed's monetary policy surprises and incorporate it into the forecasts, and its associated impacts on the financial market.

Given the importance of the central bank's monetary policy, the market participants form their expectations before the actual policies are announced to the public. Though the central banks have widely recognized the critical role of expectation management in implementing policies and devoted their efforts to improving communication with the public, the events that document the divergence between market expectations about monetary policies and actual policies are not rare in practice. Specifically, by capturing market expectations about central bank target policy rate, previous studies have well documented these divergent attitudes between central banks and market participants.

[27] This chapter is based on the working paper "Central Bank Private Information and Financial Analyst" co-authored with Wen Lin and Yang Wang. The paper has been presented in the seminar of University of Bristol.

These divergences in the monetary policies create policy surprises to the public, ranging from expansionary surprises (i.e., unexpected reduction in policy rate) to contractionary surprises (i.e., unexpected increase in policy rate) (e.g., Kuttner, 2001, Bernanke and Kuttner, 2005, Armstrong et al., 2019).

These policy surprises can further influence the expectations of the market participants in terms of both future economic conditions and the heterogenous firms' performance (Gürkaynak et al., 2004, Nakamura and Steinsson, 2018, Lunsford, 2020). One major cause of these policy surprises is the private information of the central bank. By accessing different information sources or employing different models, the central bank holds private information about economic fundamentals (e.g., Romer and Romer, 2000, Lakdawala and Schaffer, 2019). Because of the tight connection between the central bank's monetary policy, economic fundamentals and firms' performance, this central bank's private information is important to analysts. After observing the central bank's monetary policy surprise, market participants can infer the private information embedded in this surprise and further update their expectations about future economic fundamentals and monetary policy (e.g., Nakamura and Steinsson, 2018). Responding to this private information, analysts are likely to revise their forecasts accordingly to incorporate it.

For the interpretation of the central bank's private information, prior studies provide two competing theories. On the one hand, the conventional theories of monetary policy transmission generally view unexpected expansionary (contractionary) monetary policy revealed by the central bank's private information as *positive* (*negative*) news about the future economy to firms. Specifically, following recently developed theories related to the credit channel of monetary policy transmission, the unexpected expansionary (contractionary) monetary policy indicates a more (less) supply of credits to firms or lower (higher) external firms' financing premium, which in turn benefit (damage) firms' performance in the future (Bernanke and Gertler, 1995, Mishkin, 1995). However, the transmission of the monetary policy takes time, which might need around a half year or even a few years to influence the local economy (e.g., Bernanke and Gertler, 1995, Van Els et al., 2001).

On the other hand, instead of focusing on the policy action, the theories of information effects concentrate on the signal revealed by the monetary policy and predict the opposite impacts. The unexpected expansionary (contractionary) monetary policy revealed by the central bank's private information signals a *pessimistic* (*optimistic*) assessment of the current economic fundamentals endorsed by the central bank and therefore, firms' performance could be damaged (improved) in the near future (e.g., Nakamura and Steinsson, 2018, Lakdawala and Schaffer, 2019).

On the basis of the above competing theories, this chapter predicts that analysts will update their expectations by incorporating the private information embedded in the central bank's monetary policy surprises and revise their short-term earnings forecasts. If the analysts are rational (irrational) in processing macroeconomic information, theories of information effects (conventional theories of monetary policy transmission) should dominate the interpretation of the Fed's private information.

To examine the impact of central bank's private information on analysts' forecast revisions, this chapter uses the Fed funds rate surprise (i.e.. FFR surprise), which is measured by the changes in the federal funds rate futures contracts around FOMC announcements and multiplied by -1 (e.g., Kuttner, 2001, Bernanke and Kuttner, 2005, Armstrong et al., 2019). Then, by regressing the FFR surprises on the difference between the Fed's and market participants' forecasts of macroeconomic indicators, the Fed's private information is extracted from these FFR surprises (Lakdawala and Schaffer, 2019). As with the monetary policy surprise, a positive (negative) value of the Fed's private information suggests an unexpected expansionary (contractionary) monetary policy.

The empirical analysis of this chapter is based on the 176 FOMC meetings between 1989 and 2008. By regressing the analysts' forecast revisions on the Fed's private information, this chapter finds asymmetric interpretations depending on the types of monetary policies. Following an expansionary monetary policy revealed by the Fed's private information, the analysts revise their forecasts upwards, which is consistent with conventional theories of monetary policy transmission. However, this upward revision is still evident following contractionary monetary policy revealed by the Fed's private information, indicating that theories of the information effects dominate the analysts' interpretations in this case. These findings are consistent with the findings of Chapter 2 that the analysts are irrational in dealing with expansionary monetary policy. Furthermore, these conclusions are reinforced by more transparent post-FOMC meeting disclosure and FOMC meetings with reverse directions in the monetary policy.

Next, this chapter examines how task-specific experience related to FOMC meetings influences analysts' incorporation of the Fed's private information. Previous studies have found a positive association between analysts' experience and their forecast performance (e.g., Clement, 1999, Mikhail et al., 1997). Instead of using general or firm-specific experience, this chapter focuses on the task-specific experience related to the FOMC meetings (Clement et al., 2007). Given the Fed's private information is unusual to sell-side analysts who issue forecasts and recommendations about firms, the specific knowledge learnt from past FOMC meetings can benefit analysts in processing the Fed's private information.

The impact of this task-specific experience on analysts' interpretations of the Fed's private information is mixed. The macroeconomic literature reports comprehensive empirical findings related to a series of macroeconomic indicators, which support conventional theories of monetary policy transmission (Bernanke and Gertler, 1995, Kuttner, 2001). Thus, the specific knowledge learned from past FOMC meetings might make analysts observe the real impacts of the Fed's monetary policies on firms and support the conventional theories. However, this task-specific experience might also support the theories of information effects. The analysts with more professional experience in dealing with the information disseminated by the FOMC meetings would perform better in processing this information. By interacting the Fed's private information with the measurement of analyst task-specific experience, results show that when contractionary monetary policies are revealed by the Fed's private information, this task-specific experience mitigates previous analysts' upward revisions, supporting conventional theories of monetary policy transmission.

Finally, to explore the role of the analysts in transmitting central bank monetary policy to the capital market, this chapter investigates the market reaction to the analysts' forecast revisions in the light of the Fed's private information. This chapter finds that investors rely more on analysts when the Fed's private information reveals more expansionary monetary policy. Combined with the previous findings that analysts incorporate the Fed's private information, results support the role of analysts in facilitating the transmission of the central bank monetary policy.

This chapter makes three contributions to the literature. First, it contributes to the literature on the impact of central bank information on economic activities (e.g., Gürkaynak et al., 2004, Nakamura and Steinsson, 2018, Lunsford, 2020). This chapter is especially relevant to studies that explore the private information revealed by central bank disclosure (e.g., Romer and Romer, 2000, Lakdawala and Schaffer, 2019). This chapter shows that analysts incorporate the private information embedded in the Fed's monetary policy surprises into their forecasts.

Second, following the former Fed Chairwoman Ms. Yellen's recent call for the study of understanding the heterogeneity in the transmission of monetary policy, this chapter examines the market reaction to analysts' forecast revision in the light of the Fed's private information. Findings suggest that investors respond to the analysts' forecasts, which have incorporated the Fed's private information. These findings also add to the existing studies of the interaction between macro-level and micro-level entities (e.g., Gertler and Gilchrist, 1994, Konchitchki and Patatoukas, 2014, Ozdagli, 2018, Armstrong et al., 2019).

Third, this chapter adds to the literature on the relationship between analysts' characteristics and their forecast performance (e.g., Clement, 1999, Mikhail et al., 1997), and particularly on the impact of task-specific experience learned from previous events (Clement et al., 2007). Results show that task-specific experiences related to FOMC meetings influence analysts' interpretations of the Fed's private information.

This chapter proceeds as follows: Section 3.2 provides theoretical underpinning and predictions; Section 3.3 provides the predictions. Section 3.4 outlines the data selection procedure; Section 3.5 discusses the main research design; Section 3.6 reports the results and findings, and Section 3.7 concludes.

3.2. Literature review and theoretical background

3.2.1 The Fed's monetary policy and private information

The primary objectives of the Fed are to maximize employment and maintain price stability. To achieve these goals, the Fed mainly uses three policy tools: 1. The reserve requirement of banks; 2. The discount rate the Fed charges on loans borrowed by other banks; and 3. The open market operations. The most frequently used of these policy tools is open market operations.[28] To move the market interest rate close to the target Federal Funds Rate (hereafter FFR), the Fed purchases and sells securities in the open market.

In 8 scheduled meetings in a year, the Federal Open Market Committee (FOMC) sets the target FFR. The FOMC might also host unscheduled meetings to respond to necessary economic conditions and developments.[29] Before 1994, the FOMC did not disclose the target FFR determined by the current FOMC meeting to the public until the next FOMC meeting. The market participants had to infer the current target FFR on the basis of either the trading behaviour of the Fed or the press release announcing the discount rate change (Gürkaynak et al., 2004, Bernanke and Kuttner, 2005). In 1994, the FOMC changed the post-meeting disclosure mechanism by immediately disclosing the current target FFR to the public.

Following the current target FFR, the trading desk of the Federal Reserve Bank of New York executes purchase or sale transactions in the System Open Market Account. If the Fed decides to decrease the target FFR (i.e., expansionary monetary policy), the Fed's trading desk will buy securities from the U.S. commercial banks and credit the reserve accounts of other commercial banks, resulting in a larger supply of reserves. If the Fed decides to increase the target FFR (i.e., contractionary monetary policy), it will sell securities to the U.S. commercial banks and withdraw the funds from the reserve accounts of other commercial banks, leading to a smaller supply of reserves. Collectively, through

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[28] For detailed information, please see: https://www.frbsf.org/education/teacher-resources/what-is-the-fed/monetary-policy/.

[29] For instance, as a response to the outbreak of Covid-19, the FOMC hosted a unscheduled meeting on 15th March 2020 to ensure that the goals of the maximum employment and price stability are not affected. For detailed information, please see this meeting's press release: https://www.federalreserve.gov/newsevents/pressreleases/monetary20200315a.htm

open market operations, the Fed can adjust market interest rates and the funds available to commercial banks, and therefore use the monetary policy to influence the economy.

Because of the tremendous impacts on the economy, market participants form expectations about monetary policy before the Fed discloses it to the public. Though the Fed has sought to improve expectation management in the past decades, the divergence on monetary policy between the market participants and the Fed is still significant (e.g., Kuttner, 2001). This divergence leads to monetary policy surprises for the public. Given the tight connection between the Fed's monetary policy and the economy, previous studies find the market participants' reaction to the monetary policy surprises, indicating the incorporation of these policy surprises to update market expectations (e.g., Bernanke and Kuttner, 2005, Armstrong et al., 2019).

One important cause of monetary policy surprises is the information asymmetry between market participants and the central bank. The macroeconomic literature argues that, because it accesses different information sources and models, the central bank has private information about economic conditions that is not available to the public (e.g., Barro, 1976, Barro and Gordon, 1983). This private information is relevant to market participants. Once they have information about actual monetary policy, market participants can infer the private information embedded in monetary policy surprises and update their expectations (Lakdawala and Schaffer, 2019, Romer and Romer, 2000, Campbell et al., 2017, Nakamura and Steinsson, 2018).

3.2.2 Interpretation of the central bank's private information

The impacts of monetary policy on firms' performance are controversial, leading to mixed interpretations of embedded private information. First, conventional theories of monetary policy transmission indicate that, through different channels, an expansionary (contractionary) monetary policy benefits (damages) firms' performance. The traditional theory of the interest rate channel implies that given some degree of price stickiness, an expansionary (contractionary) monetary policy leads to a decrease (increase) in the real interest rate and influences firms' performance via higher (lower) consumption or spending on investment (e.g., Rotemberg and Woodford, 1997). However, previous studies have suggested that the observed impacts of monetary policies in the financial market seem to go beyond the interest rate channel (Kuttner and Mosser, 2002, Boivin et al., 2010).

To respond to the call for further understanding of how monetary policy is transmitted and complements the interest rate channel, theories of the credit channel have been developed. This particular channel assumes that there is information asymmetry between the borrower and lender, which leads to external financing premium for the borrowers. By influencing the external financing premium and loanable funds for borrowers, the central bank's monetary policy can affect the economy. Depending on whether one adopts the perspective of the lenders or borrowers, this credit channel can be further classified into the bank lending channel and the balance sheet channel (Kuttner and Mosser, 2002).

The bank lending channel posits that an expansionary (contractionary) monetary policy leads to more (less) available loans that commercial banks can make to firms and, therefore, benefits (damages) firms' earnings (Bernanke and Gertler, 1995). This channel emphasizes the importance of the lending relationship between banks and borrowers in addressing the information asymmetry and the crucial role of the banks as credit providers in transmitting monetary policy. However, because of the supplier of marginal credits, sources of loanable funds and bank lending channels have changed since the deregulation and innovation in the U.S. banking industry (e.g., Woodford, 2010), the basic assumptions of the bank lending model might be difficult to hold in practice (Bernanke and Blinder, 1988) and the importance of this particular channels has been questioned (Romer and Romer, 1989, Lown and Morgan, 2002).

As a comparison, the balance sheet channel shifts the attention from the bank's lending capacity to the firm's net income and net worth. A higher interest rate caused by a contractionary monetary policy decreases a firm's net worth, which exacerbates the adverse selection and induces the firm to take excessive risk, leading to moral hazard issues. Furthermore, this higher interest rate makes a firm incur higher interest expenses, so it makes a firm have lower internal funds and rely more on external funds. Combined with the asymmetric information between firms and lenders, all of these negative impacts lead to higher external financing premium, curtail economic activities, and eventually damage firms' earnings (e.g., Bernanke and Gertler, 1995, Boivin et al., 2010). Taken together, under conventional theories of monetary policy transmission, an expansionary (contractionary) monetary policy as revealed by the central bank's private information is positive (negative) news for the market.

Second, in contrast to the conventional theories of monetary policy transmission, theories of the information effect suggest that an expansionary (contractionary) monetary policy is detrimental (beneficial) to firms' earnings. Rather than focusing on the action of the monetary policy, the theories of information effects emphasize the signal revealed by the monetary policy. The central bank's monetary policy can signal information about the economic fundamentals to the market, and thus enabling the market participants to update their expectations accordingly (e.g., Cukierman and Meltzer, 1986, Melosi, 2017). Specifically, this strand of the literature argues that the central bank implements expansionary (contractionary) monetary policies when the economic conditions are bad (good). Therefore, an expansionary (contractionary) monetary policy signals bad (good) economic conditions in the near future, and this is the message to the public which has been endorsed by the central bank.

Due to its unique position in the local economy, the central bank is the focal point for the public and has a significant influence on market expectations (Morris and Shin, 2002). If the signal conveyed by the central bank's private information makes market participants pessimistic (optimistic) about the future, they might decrease (increase) investment and consumption, and therefore damage (benefit) firms' earnings (e.g., Romer and Romer, 2000, Nakamura and Steinsson, 2018). In general, the theories of information effects suggest that an expansionary (contractionary) monetary policy as revealed by the central bank's private information is negative (positive) news to the market.

The conventional theories of monetary policy transmission and the theories of information effects predict two competing impacts on firms' performance, and the ultimate outcome will depend on the relative strength of these two competing effects. Previous macroeconomic studies have well documented the empirical findings related to crucial macroeconomic indicators, such as inflation, interest rate, GDP and housing, are consistent with conventional theories of monetary policy transmission (e.g., Bernanke and Gertler, 1995, Kuttner, 2001, Iacoviello and Minetti, 2008). Apart from that, previous studies generally show that an expansionary monetary policy leads to an increase in the stock index, suggesting that the stock market interprets monetary policy in line with the conventional theories (Bernanke and Kuttner, 2005, Armstrong et al., 2019, Lakdawala and Schaffer, 2019).

Compared with conventional theories, the empirical evidence on information effects is relatively limited. The seminal work of Romer and Romer (2000) shows that the Fed holds substantial private information about the path of the economy, and the commercial forecast agencies revise their expectations of inflation in response to the Fed's monetary policy following the theories of information effects. Consistent with Romer and Romer (2000), later studies find that contractionary monetary policy makes commercial forecast agencies revise down expectations of unemployment (Campbell et al., 2012) and revise up expectations of GDP (Nakamura and Steinsson, 2018).

3.3. Hypothesis development

Because of its significant impact on firms' performance, analysts take monetary policy into consideration when making forecasts. To investigate how analysts interpret the Fed's private information, this chapter chooses to focus on short-term earnings forecast revisions. Forecast revisions are signed, and by revising forecasts up or down, it can determine whether analysts view a particular type of monetary policy as revealed by the Fed's private information as good or bad news to the firm.

Figure 3.1 shows the theoretical framework of how analysts interpret the Fed's private information and revise their earnings forecasts. Though theories of monetary policy transmission and information effects can both explain how the Fed's private information is interpreted, the forecasting horizons revealed by these two theories are different. Previous studies of conventional monetary transmission theories indicate that monetary policy needs more than a half year or even a few years to influence the local economy (e.g., Bernanke and Gertler, 1995, Van Els et al., 2001). Thus, in accordance with conventional theories of monetary policy transmission, the Fed's private information reveals the possible economic conditions in the long-term. On the other hand, the theories of information effects interpret monetary policy on the basis of the current economic condition. Consequently, following the theories of information effects, the Fed's private information reveals the possible economic conditions in the short-term.

[Insert Figure 3.1]

If the analysts are rational in processing macroeconomic information when making short-term forecasts, the theories of information effects should dominate the interpretation of the Fed's private information. This prediction suggests that the analysts should view expansionary monetary policy revealed by the Fed's private information as bad news for firms since this expansionary monetary policy implies a pessimistic view of the overall economy, and they will revise down the firms' short-term earnings forecasts.

However, previous studies indicate that analysts are not specialists in processing macroeconomic information and may make poor forecasts (e.g., Hope and Kang, 2005, Hugon et al., 2015). Therefore, the analysts might be irrational in processing macroeconomic information and interpret the Fed's private information in accordance with the conventional theories of monetary policy transmission. In other words, they view expansionary monetary policy as revealed by the Fed's private information as good news for firms and they will revise up firms' short-term earnings forecasts. Based on the above arguments, this chapter presents two competing hypotheses:

H1a: Analysts follow the theories of information effects to revise up (down) short-term earnings forecasts following contractionary monetary policy (expansionary monetary policy) revealed by the Fed's private information.

H1b: Analysts follow the conventional theories of monetary policy transmission to revise up (down) short-term earnings forecasts after expansionary monetary policy (contractionary monetary policy) revealed by the Fed's private information.

3.4. Sample selection

Table 3.1 presents the sample selection. The measurement of the Fed's private information is based on the federal funds future rate. The federal funds futures market was established in 1989, so the sample starts in 1989. The sample ends in 2008 because the target Federal fund rate was the primary policy instrument before the financial crisis. Following previous studies (e.g., Bernanke and Kuttner, 2005), the unscheduled meeting that was held after the 9/11 terror attack has been removed from the sample to avoid noise and bias.

The analyst forecast data has been obtained from the I/B/E/S Detail File. Observations with forecasts not in U.S. dollars, and missing information on analysts' identifiers and forecasts are excluded. To examine the analysts' forecast revisions, this chapter focuses on their one-quarter-ahead forecasts. For each firm-analyst-forecast period end pair, the final forecast before an FOMC meeting and the first forecast after the same FOMC meeting are selected to avoid the impacts of any other concurrent macroeconomic shocks.

For the investigation of the market reaction to analysts' forecast revisions, the sample further excludes observations of cases in which the three-day window of a revision event overlaps with others. Apart from that, the sample includes observations with firms' financial information from Compustat, stock price information from CRSP and analysts' information from I/B/E/S. Furthermore, considering the fact that the impact of monetary policy on utilities and financial firms could be different from other firms, these two types of firm are excluded. This selection process leads to a sample with 223,194 observations for the tests of the forecast revisions and 91,672 observations for the test of the market reaction.

[Insert Table 3.1]

3.5. Empirical design

3.5.1. Measuring private information

According to Gürkaynak et al. (2004), a monetary policy surprise is constructed by using five future contracts: the current month's Fed funds futures, the 3-month ahead Fed funds futures, and the 2-quarter, 3-quarter, and 4-quarter ahead Eurodollar futures. Compared with the method of Bernanke and Kuttner (2005) used in Chapter 2, which uses only the current month's Fed funds futures, including the other 4 Fed funds rates and

Eurodollar futures contracts in the calculation could better capture the market's expectations about future Fed fund rates actions and more private information embedded in the Fed's monetary policy. The surprise in each contract is measured as the daily changes in the future rates around an FOMC meeting.

To summarize all the information about the Fed's fund rates in these 5 contracts in a parsimonious way, this chapter computes the first component of these 5 surprises implied by these future contracts after performing the principal component analysis. The first principal component could explain more than 80% of the total variation across all these contracts. To assist the interpretation, this first principal component is multiplied by -1 (*Total surprise*). This *Total surprise* is the Fed's total monetary policy surprise and contains information about the short and medium-term path of expected interest rates. A positive (negative) *Total_surprise* indicates an unexpected expansionary (contractionary) monetary policy, which means an unexpected reduction (increase) in the FFR.

Next, the private information component is extracted from the total monetary policy surprise. Similarly to the method used in Barakchian and Crowe (2013) and Campbell et al. (2017), the Fed's private information is measured as the differences between the FOMC Greenbook forecasts and the private sector Blue Chip forecasts. Greenbook forecasts are constructed by the internal Federal Reserve Board's staff a week prior to each scheduled FOMC meeting and are released to the public with a five-year lag.[30] Blue Chip forecasts are compiled by representative market institutions on a monthly basis and released on the 10th of each month. Thus, the measure of private information is calculated as the most recent Greenbook forecasts minus the Blue Chip forecast prior to the FOMC meeting.[31]

This chapter uses the forecasts of 4 variables to reflect the macroeconomic condition: real GDP, CPI, industrial production and the civilian unemployment rate. For each

[30] The five-year lagged public disclosure eliminates contamination in the Blue Chip forecasts. If the Greenbook forecasts are publicly available in time, the Blue Chip forecasts could incorporate the information spilled from the Greenbook forecasts. In this case, the forecasts from the Blue Chip would also contain the private information about the economy.

[31] For example, for a scheduled FOMC meeting on the 22nd of a month the Greenbook forecast released a week prior to this meeting (the 15th of this month) and the Blue Chip forecast released on the 10th of the same month are used.

variable, both sets of forecasts provide five different forecast horizons: the current quarter forecast, one-quarter ahead forecast, two-quarter ahead forecast, three-quarter ahead forecast, and four-quarter ahead forecast. Following Lakdawala and Schaffer (2019), the current and third-quarter ahead forecasts of these four variables are used to represent the short window and long window of the macroeconomy.[32]

Finally, following Lakdawala and Schaffer (2019), this chapter regresses the Fed's total monetary policy surprise on the private information component constructed by the differences between the FOMC Greenbook and Blue Chip forecasts to extract the Fed's private information component from the total monetary policy surprise. Thus, the fitted value of this regression is denoted as the Fed's private information revealed by the monetary policy surprise (*Surprise_Private info*). Consistent with the total monetary policy surprise, a positive (negative) *Surprise_Private info* indicates an unexpected expansionary (contractionary) monetary policy.

3.5.2. Model specification

Analysts' forecast revisions (*FR*) are defined as the first forecast after an FOMC meeting minus the final forecast before the same FOMC meeting, scaled by a firm's stock price prior to the revision. These two forecasts are issued by the same analyst for the same firm with identical forecast period end. This chapter investigates the analysts' interpretation of the Fed's private information by regressing the analysts' forecast revisions on the Fed's private information. Specifically, the following regression model is estimated:

$$FR = \beta_0 + \beta_1 \cdot Surprise\ Private\ info + Analyst\ Controls + Broker\ Controls \\ + Firm\ Controls + Macro\ Controls + \gamma_t + \theta_j + \varepsilon_0 \qquad (3.1)$$

Following previous studies (e.g., Hugon et al., 2015, Amiram et al., 2018), four sets of control variables are included in the regression model. First, the regression model controls for analyst characteristics, including forecast horizon (*HORIZON*), number of industries

[32] Lakdawala and Schaffer (2019) use the current quarter and the fourth-quarter ahead forecasts since these two measures have the weakest correlation in their sample. For this chapter, the current quarter and the third-quarter ahead forecasts show the weakest correlation.

(*NIND*), number of firms (*NFIRM*), and firm-specific experience (*FEXP*). Second, the regression model controls for the impact of brokerage houses by using the brokerage firm size (*BSIZE*). Third, the regression model includes firm-level characteristics as control variables, including total accruals (*LAG_TACC*), profitability (*LAG_PROFIT*), and firm size (*LAG_SIZE*). Four, the regression model controls for macroeconomic factors, including inflation rate (*LAG_INFLATION*) and GDP (*LAG_GDP*). All continuous variables are winsorized at the top and bottom 1 percent, and detailed definitions of all variables are included in Appendix 3.1. Finally, the regression model includes year fixed effects γ_t, and firm fixed effects θ_j. The regression model is estimated by using OLS regression and standard errors are clustered by firm.

For the regression results, if the coefficient on the variable *Surprise_Private info*, β_1, is positive (negative) and significant, it indicates that analysts interpret the Fed's private information following the conventional theories of monetary policy transmission (theories of information effects).

3.6. Results

3.6.1 Descriptive statistics

Panel A in Table 3.2 presents descriptive statistics for the Fed's total surprise (*Total surprise*) and private information component (*Surprise_private info*). During the sample period, the Fed held 176 FOMC meetings, including scheduled and unscheduled meetings. Out of these 176 meetings, 77 meetings released unexpected expansionary news in their private information captured as the *Positive Surprise_private info*, and 99 meetings released unexpected contractionary news in their private information captured as the *Negative Surprise_private info*. The mean values of *Total surprise* and *Surprise_private info* are negative, indicating that contractionary monetary policies revealed by the total monetary policy surprise and the Fed's private information. The distributions of these two surprises with opposite signs are similar in their average magnitudes and variations. Panel B in Table 3.2 presents descriptive statistics for other variables in the positive surprise and negative surprise sub-samples, respectively. On average, analysts revise their forecasts down, and the accumulative abnormal returns around forecast revision dates are also negative. The mean values of control variables show a similar tendency in these three samples.

[Insert Table 3.2]

3.6.2 Analysts' interpretation of the Fed's private information

Table 3.3 presents the regressions result of Eq. (3.1) after splitting them into the samples of expansionary and contractionary monetary policies revealed by the Fed's private information. Column 1 shows that, for the expansionary monetary policy revealed by the Fed's private information, the coefficient on *Surprise_Private info* is positive and significant (coef=0.109; t-stat=3.41), suggesting that following expansionary monetary policy, analysts revise the forecasts up. This finding supports the H1b that analysts are irrational in processing the macroeconomic information and interpret the Fed's private information in line with the conventional theories of monetary policy transmission. This result is also consistent with the finding of Table 2.3, which suggests that analysts are irrational in processing expansionary monetary policy and make biased forecasts. Furthermore, this finding is consistent with prior studies (e.g., Bernanke and Kuttner, 2005, Lakdawala and Schaffer, 2019), and indicates that, in general, analysts view expansionary monetary policy as positive news for the firms and their interpretations follow the conventional theories of monetary policy transmission (e.g., Armstrong et al., 2019).

Column 2 reports the regression results using the sample of contractionary monetary policies revealed by the Fed's private information. By contrast to the sample of expansionary monetary policies, the coefficient on *Surprise_Private info* is negative and significant (coef=-0.106; t-stat=-4.73), indicating that analysts still revise up the forecasts as a response to the contractionary monetary policies revealed by the Fed's private information. This finding supports the H1a, and in this case, the analysts believe that the contractionary monetary policy revealed by the Fed's private information signals a growing economy in the near future and, therefore, they view this private information as positive news. This interpretation of contractionary monetary policy follows the theories of information effects (e.g., Romer and Romer, 2000, Nakamura and Steinsson, 2018).[33] In terms of economic significance, a 1% increase (decrease) in the value of the Fed's private information makes analysts revise their forecasts up by 0.11% (0.11%) for expansionary monetary policy (contractionary monetary policy), which accounts for 42.3% and 52.3% of the difference of the forecast revision between the first and second quartile, respectively.[34]

Columns 3 and 4 report the regression results for using total monetary policy surprise rather than private information. As shown in these two columns, none of the coefficients on *Total Surprise* are significant for both expansionary and contractionary monetary policies. These findings indicate that the analysts are particularly sensitive to the private information revealed by the Fed, which is consistent with prior findings of different market reactions to the Fed's total monetary policy surprise and its private information (Lakdawala and Schaffer, 2019).

However, the findings of insignificant coefficients on *Total Surprise* appear to be inconsistent with the results of biased forecasts presented in Chapter 2. These inconsistent findings are mainly due to the difference in the construction of the surprise variable and regression sample. First, while the policy surprise of Chapter 2 is constructed on the basis of the current month's federal funds future contracts, the total surprise of Chapter 3 includes future contracts with longer periods to further capture the private information component. Second, the regression sample of Chapter 2 includes both the first forecast and the revised forecast made by the analysts following the FOMC meeting. As a comparison, the regression sample of Chapter 3 only includes revised forecasts.

In general, the main regression results show that the conventional monetary policy transmission channel dominates the information effects channel when analysts interpret an expansionary monetary policy, while the information effects channel dominates the conventional monetary policy channel when they come across a contractionary policy. As in Chapter 2, there are concerns of endogeneity that the surprise variable might reflect

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[33] Additionally, the regression model controls for the latest earnings surprise. The results from this untabulated analysis are qualitatively similar to the main results of Table 3.3.

[34] The differences in the forecast revision between the first quartile and the second quartile are 0.26% and 0.21% for expansionary and contractionary samples.

macroeconomic uncertainty. Following the methods discussed in Chapter 2, this chapter uses a daily window when constructing this surprise variable and includes crucial macroeconomic factors (i.e., lagged GDP and inflation) in the regression model.

[Insert Table 3.3]

Next, this chapter explores how analysts' forecast revisions as a response to the Fed's private information vary across different types of FFR surprises. First, the Fed significantly changed its post-meeting disclosure in 1994. Prior to this change, the Fed did not disclose the target FFR and market participants had to infer it from other sources of information. To improve transparency in communication, the Fed started to disclose the target FFR immediately after the FOMC meeting from 1994. A more transparent disclosure of monetary policy information might make it easier for analysts to incorporate the Fed's private information.

To explore the impact of this change in post-meeting disclosure, the regression model further interacts the *Surprise_Private info* with a dummy variable of 1994 (*Post_1994*). As shown in Table 3.4, the coefficients on the interaction term between *Surprise_Private info* and *Post_1994* are significant and positive (negative) for the expansionary (contractionary) monetary policy sample (coef=0.176, t-stat=2.61; coef=-0.294, t-stat=-2.99). Consistent with previous studies (e.g., Bernanke and Kuttner, 2005), the impacts of the Fed's monetary policies are mainly driven by the FOMC meetings with transparent disclosure in post-1994 periods. In this case, the transparent post-FOMC meeting disclosure facilitates the incorporation of the Fed's private information into analysts' forecasts.

[Insert Table 3.4]

Second, there are 8 FOMC meetings that changed the direction of actual monetary policies relative to the previous meetings. Compared with "usual" meetings, these 8 FOMC meetings with reverse monetary policies are more likely to update market expectations about monetary policies and might have larger impacts on analysts' forecast revisions. To examine variations among FOMC meetings, the regression model further interacts *Surprise_Private info* with a dummy variable of *Reverse direction*. Table 3.5 column 2 shows that the coefficient on the interaction term between *Surprise_Private info* and *Reverse direction* is negative and significant for the negative private information sample (coef=-0.199, t-stat=-2.06). This finding suggests that analysts further incorporate contractionary monetary policy as revealed by the FOMC meetings with reverse monetary policies.

[Insert Table 3.5]

3.6.3 The impact of analyst task-specific experience

This section investigates the impact of analysts' characteristics on the incorporation of the Fed's private information and primarily focuses on their task-specific experience. On the one hand, the Fed's monetary policy surprises indeed reveal private information that is relevant to the analyst. On the other hand, previous studies find that analysts are not good at processing macroeconomic information (Hope and Kang, 2005, Hugon et al., 2015). This problem might be mitigated by the past working experience of analysts. The analyst literature shows that more experienced analysts tend to have better forecast performance (e.g., Mikhail et al., 1997, Clement, 1999).

Rather than focusing on general or firm-specific experience, this chapter chooses task-specific experience. Although the learning-by-doing theory implies that working experience is beneficial to analysts, the knowledge and skills they have learned from past events might not always be useful in other situations (Clement et al., 2007). Given that the analysts in this chapter are sell-side, and issue forecasts and recommendations about commercial firms rather than macroeconomic policies and conditions, the Fed's private information from FOMC meetings represents unusual knowledge. The specific experience learned from working with the FOMC meetings can truly benefit analysts in terms of processing the Fed's private information.

The impact of analysts' task-specific experience on the interpretation of the Fed's private information is an open question. Generally, previous studies have reported comprehensive findings of correlations between central bank monetary policies, macroeconomic indicators and stock market reactions via the conventional monetary policy transmission channel (e.g., Bernanke and Kuttner, 2005, Armstrong et al., 2019). Therefore, more specific experience related to the FOMC meetings should make analysts understand the real impact of monetary policies on firms' performance better, which would make their interpretations follow conventional theories of monetary policy transmission more closely.

However, this specific experience related to the FOMC meetings might also facilitate the interpretation of the Fed's private information via the information effects channel. Even though the Fed's private information is useful, fully understanding it might not be an easy task. In particular, the impact of the Fed's private information is in contrast to conventional wisdom, incorporating this into forecasts requires analysts to have more relevant working experience. The more experience they have of FOMC meetings, the better they may be able to process the Fed's private information and incorporate it into their forecasts.

To measure the analysts' specific experience related to FOMC meetings, this chapter employs a method of constructing task-specific experience based on Clement et al. (2007), which counts the number of FOMC meetings an analyst has experienced from year-5 to year-1 before the current FOMC meeting (*TASKEXP*). The larger the value of *TASKEXP*, the more specific experience related to FOMC meetings an analyst has. When constructing the *TASKEXP* for an analyst, this chapter considers 2 types of FOMC meetings: 1. Unscheduled FOMC meetings; and 2. FOMC meetings with non-zero monetary policy surprises. These FOMC meetings contain more information than other meetings about unexpected macroeconomic changes. To investigate the impact of analysts' specific experience related to FOMC meetings on the forecast revision, the following regression model is used:

$$\begin{aligned} FR = {} & \beta_0 + \beta_1 \cdot Surprise\ Private\ info + \beta_2 \cdot TASKEXP + \beta_3 \\ & \cdot Surprise\ Private\ info \cdot TASKEXP + Analyst\ Controls \\ & + Broker\ Controls + Firm\ Controls + Macro\ Controls + \gamma_t + \theta_j \\ & + \varepsilon_0 \qquad (3.2) \end{aligned}$$

TASKEXP is the number of FOMC meetings an analyst has experienced from year-5 to year-1. FOMC meetings are those meetings with non-zero monetary policy surprises or unscheduled meetings. Following Eq. (3.1), the regression model includes the same control variables and the same set of fixed effects. The regression model is estimated by using OLS regression and standard errors are clustered by firm.

Table 3.6 columns 2 and 4 report the regression results for the samples of contractionary monetary policies. Consistent with the results in Table 3.3, the coefficients on *Surprise_Private info* are still negative and significant, indicating that the analysts' interpretations follow the theories of information effects. However, the coefficients on the interaction term between *Surprise_Private info* and *TASKEXP* are positive and significant. These findings show that task-specific experience mitigates the analysts' upward revisions following contractionary monetary policy revealed by the Fed's private information and suggest that the analysts with more specific experience related to FOMC meetings are less likely to follow the theories of information effects to interpret the Fed's private information.

However, columns 1 and 3 show that the coefficients on the same interaction term are insignificant for the sample of expansionary monetary policy revealed by the Fed's private information. This finding shows that the specific experience related to FOMC does not play a major role when the interpretations have already followed conventional theories of monetary policy transmission. Collectively, the results from Table 3.6 seem to indicate that the knowledge that analysts have learned from past FOMC meetings supports the conventional theories of monetary policy transmission.

[Insert Table 3.6]

3.6.4 Market reaction to forecast revision

Finally, this chapter investigates how analysts' forecast revisions play a role in the Fed's monetary policy transmission by examining the market reaction to the analysts' forecast revisions in the light of the Fed's private information. Considering the additional yet crucial information from the Fed, this private information revealed by unexpected policy surprises is likely to introduce uncertainty to the market. Because uncertainty makes the task of firm valuation more complex, investors might rely more heavily on analysts. This is confirmed by previous studies which have found that with the heightened market uncertainty, investors are more responsive to analysts' forecasts (Amiram et al., 2018, Loh and Stulz, 2018). This chapter therefore predicts that when more expansionary or contractionary monetary policy is revealed by the Fed's private information, investors' responsiveness to the analysts' forecast revisions increases. Empirically, this issue is examined by using the following equation:

$$
\begin{aligned}
CAR\ (-1,+1) = {} & \beta_0 + \beta_1 \cdot Revision + \beta_2 \cdot Abs\ Surprise\ Private\ info + \beta_3 \\
& \cdot Revision \cdot Abs\ Surprise\ Private\ info + Analyst\ Controls \\
& + Broker\ Controls + Firm\ Controls + Macro\ Controls \\
& + Stock\ controls + \delta_i + \gamma_t + \varepsilon_0 \qquad (3.3)
\end{aligned}
$$

In this regression model, *CAR (-1, +1)* is the three-day cumulative abnormal return around the date that an analyst revises the forecast for a firm. *Revision* is the analysts' forecast revisions, which are the same as Eq. (3.1) and (3.2). To measure the private information revealed by the Fed, rather than using the signed variable of *Surprise_Private info*, the regression model uses the absolute value of the Fed's private information (*Abs_Surprise_Private info*). Therefore, the model uses the interaction of *Revision* with the *Abs_Surprise_Private info* to examine the impact of the Fed's private information on the investors' responses to analysts' forecast revisions. Following Eq. (3.1) and (3.2), the regression model includes the same controls of analyst, broker, firm and macroeconomic factors. Additionally, the regression model controls for the firm stock return volatility prior to the forecast revision (*RET_SD*) and stock market momentum (*MOML*). Finally, the regression model includes Fama-French 48 industries fixed effects and δ_i, year fixed effects, γ_t. The regression model is estimated by using OLS regression and standard errors are clustered by analyst-firm and year.

Consistent with previous studies, the results reported in Table 3.7 columns 1 and 2 show that the coefficients on *Revision* are positive and significant, indicating that investors respond to the analysts' forecast revisions (e.g., Hilary and Shen, 2013, Hugon et al., 2015). Furthermore, column 1 reports that the coefficient on the interaction term between *Revision* and *Abs_Surprise_Private info* is positive and significant (coef=0.065, t-stat=1.78), suggesting that when more expansionary monetary policies are revealed by the Fed's private information, investors rely more on analysts' forecasts. Combined with the findings in the previous section, this chapter finds that the analysts incorporate the Fed's private information into their forecasts, and in the meantime, the Fed's private information makes investors seek more advice about firms from analysts. By processing and disseminating the Fed's private information, the analysts facilitate the transmission of monetary policy.

As a comparison, column 2 shows that the coefficient on the same interaction term is insignificant, suggesting that investors do not respond differently to analysts' forecast revisions when more contractionary monetary policies are revealed by the Fed's private information. Previous studies generally indicate that investors follow the conventional theories of monetary policy transmission to interpret the Fed's monetary policies, which is contradictory to the theories of information effects which are followed by the analysts in contractionary policy sample (e.g., Bernanke and Kuttner, 2005, Lakdawala and Schaffer, 2019). Overall, this chapter finds evidence to support the role of analysts in facilitating the transmission of central bank monetary policy.

[Insert Table 3.7]

3.7. Conclusion

This chapter examines how analysts interpret the private information embedded in the Fed's monetary policy surprises and how they incorporate this private information into their forecasts. Based on the FOMC meetings, this chapter finds that depending on whether the monetary policy revealed by the Fed's private information is expansionary or contractionary, analysts follow different theories to interpret and incorporate this private information. While they follow conventional theories of monetary policy transmission to revise up the forecasts to incorporate an expansionary monetary policy, they follow the theories of information effects to incorporate a contractionary monetary policy, which still leads to upward revision.

Next, this chapter examines the impact of the analysts' specific experience in relation to FOMC meetings on forecast revision. It finds that what they have learned from the previous FOMC meetings with non-zero surprises and unscheduled FOMC meetings reduces upward revisions following contractionary monetary policy revealed by the Fed's private information, supporting the conventional theories of monetary policy transmission.

Finally, this chapter examines the market reaction to analysts' forecast revisions in the light of the Fed's private information. It finds that investors rely on analysts more when there the Fed reveals more private information about economic conditions and monetary policies. Combined with previous findings with regard to analysts incorporating the Fed's private information, these results show the important role of analysts in facilitating the transmission of central bank monetary policy.

As in the case of Chapter 2, the findings of this chapter have limitations. First, because the research setting is FOMC open market operation, it might not be possible to generalize the findings of this chapter and apply them to the period when unconventional monetary policies were implemented. Second, the construction of total surprise and the Fed's private information might still capture macroeconomic uncertainty, and a more sophisticated empirical design should be considered. Third, this chapter presents some preliminary evidence to suggest that analysts might be irrational in processing the Fed's private information and use asymmetric ways of interpreting it. However, the empirical analysis of this chapter does not explore the source of this irrational behaviour and why analysts use asymmetric methods for their interpretation. This requires further investigation.

Taken as a whole, this chapter shows that analysts interpret and incorporate the private information revealed by the Fed. The findings of this chapter have policy implications for central banks and other regulators in terms of managing central bank communication and understanding how central bank monetary policy influences market expectations.

Appendix 3.1: Variable definitions

Variable	Definition	Data source
Dependent variables		
Revision	First forecast issued after an FOMC meeting minus the last forecast issued by the same analyst for the same firm and the forecast period end prior to the same FOMC meeting, scaled by a firm's stock price prior to the forecast revision.	I/B/E/S and CRSP
CAR (-1, +1)	Three-day cumulative abnormal return around the date that analysts revise their forecasts for a firm. The abnormal return is the difference between the daily return of a firm and the value-weighted market index. If any day in this three-day window is not a trading day, we select the next available trading day.	I/B/E/S and CRSP
Test variables		
Total surprise	Total monetary policy surprise measured as the first principal component of daily changes in the future rates of the current month's fed funds futures, the 3-month ahead fed funds futures, and the 2-quarter, 3-quarter, and 4-quarter ahead Eurodollar futures around an FOMC meeting, multiplied by-1.	Datastream
Surprise_Private info	Fitted value of a regression of total monetary policy surprise on the difference between the FOMC Greenbook forecasts and the private sector Blue Chip forecasts with regards to the current and third-quarter ahead forecasts of real GDP, CPI, industrial production and the civilian unemployment rate.	Blue Chip and Datastrem
Reverse direction	A dummy variable equals to 1 for observations which target funds rate from the most recent FOMC has the opposite direction compared with the previous ones, 0 otherwise.	Fed
Post_1994	A dummy variable equals to 1 for FOMC meetings beginning with February 1994, 0 otherwise.	Fed

Appendix 3.1: Variable definitions (continued)

Variable	Definition	Data source
Test variables		
Specific experience	Number of FOMC meetings an analyst has experienced from year-5 to year-1 prior to the current FOMC meeting. We consider 2 types of FOMC meetings: 1. Unscheduled FOMC meetings; 2.FOMC meetings with non-zero total monetary policy surprise.	I/B/E/S and Fed
Control variables		
NFIRM	Number of firms that an analyst follows during the quarter.	I/B/E/S
NIND	Number of Fama-French 48 industries that an analyst follows during the quarter.	Compustat
HORIZON	Number of days between the analyst's earnings forecast date and the firm's announcement date for the quarter.	I/B/E/S
FEXP	Number of quarters for which an analyst has issued at least one earnings forecast for the firm prior to the quarter.	I/B/E/S
BSIZE	Number of unique analysts employed by an analyst's brokerage house during the quarter.	I/B/E/S
LAG_TACC	Firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter.	Compustat

Appendix 3.1: Variable definitions (continued)

Variable	Definition	Data source
<u>**Control variables**</u>		
LAG_PROFIT	Firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter.	Compustat
LAG_SIZE	Natural logarithm of the market value of equity in the prior quarter.	Compustat
RET_SD	Standard deviation of daily stock returns over the past 150 days.	CRSP
MOML	Exponentially weighted (3-month half-life) cumulative return over the past 11 months.	CRSP
LAG_INFLATION	U.S. 12-month inflation rate in the prior month.	Bureau of Labor Statistics
LAG_GDP	Natural logarithms of U.S. GDP in billions of USD in the prior quarter.	St. Louis Fed

Figure 3.1. Theoretical framework

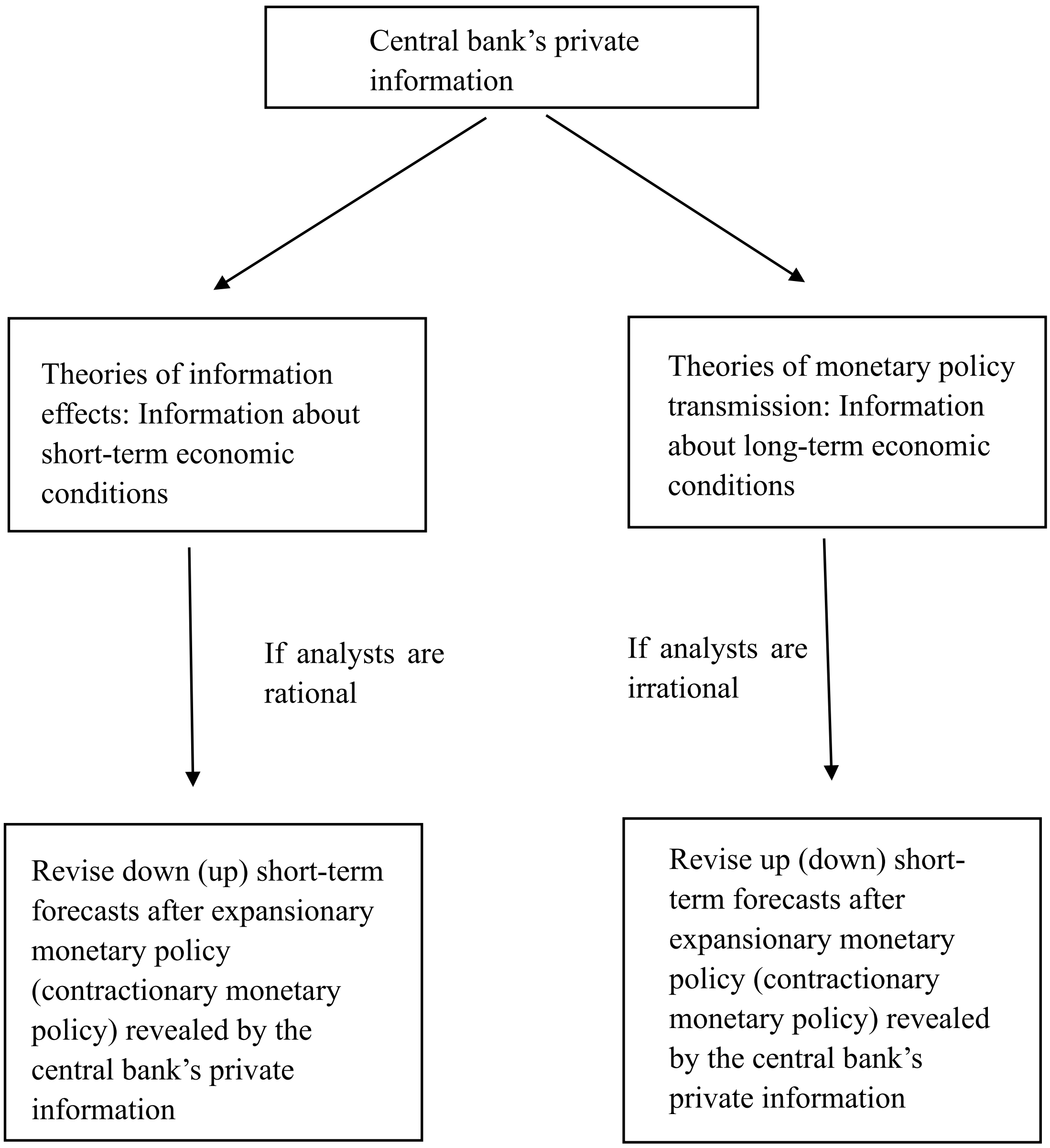

Table 3.1. Sample Selection

	Forecast revision	CAR
Initial sample: I/B/E/S initial one-quarter-ahead earnings forecasts, 1989-2008	1,739,206	1,739,206
Remaining		
Retain: earnings forecasts issued in USD, identified analysts, and non-missing estimated value and actual value	1,585,205	1,585,205
Retain: two earnings forecasts to the same period end by one analyst for one firm around an FOMC meeting	279,458	279,458
Retain: earnings forecasts with non-missing CRSP price to deflate the and SIC	275,483	275,483
Retain: earnings forecasts with available data to compute the control variables	253,158	253,158
Retain: non-financial institutions and non-utilities	223,194	223,194
Retain: earnings forecasts with no overlap with other analysts' event windows		91,672
Table 3.3	57,929-165,265	
Table 3.4	84,867-138,327	
Table 3.5	84,867-138,327	
Table 3.6	35,191-66,576	
Table 3.7		35,935-55,737

This table presents the sample selection for the analyses in Tables 3.3, 3.4, 3.5, 3.6 and 3.7. The sample period is from 1989 to 2008.

Table 3.2. Descriptive Statistics

Panel A: Fed's private information

	#Obs	Mean	SD	Min	P25	P50	P75	Max
Total surprise (%)	176	-0.0165	1.76463	-4.8423	-0.7918	-0.4041	0.2485	10.7520
Surprise_private info (%）	176	-0.0165	0.6575	-1.6397	-0.3671	-0.1204	0.3450	1.8931
Positive *Surprise_private info (%)*	77	0.5523	0.4938	0.0108	0.1346	0.3968	0.8446	1.8931
Negative *Surprise_private info (%)*	99	-0.4589	0.3620	-1.6397	-0.6084	-0.3332	-0.2095	-0.0087

Panel B: Other variables

	Positive Private Info (Expansionary)			Negative Private Info (Contractionary)		
	#Obs	Mean	Median	#Obs	Mean	Median
REVISION	84,867	-0.5311	-0.0640	138,327	-0.3980	-0.0339
CAR	35,935	-0.0054	-0.0713	55,737	-0.2076	-0.1312
NFIRM	84,867	12.7014	12.0000	138,327	12.3860	12.0000
NIND	84,867	5.3167	5.0000	138,327	5.0698	4.0000
FEXP	84,867	8.9662	6.0000	138,327	9.0632	6.0000
HORIZON	84,867	34.0601	31.0000	138,327	30.3483	27.0000
BSIZE	84,867	47.5133	40.0000	138,327	46.7823	41.0000
LAG_TACC	84,867	-0.0413	-0.0365	138,327	-0.0418	-0.0334
LAG_PROFIT	84,867	0.0115	0.0139	138,327	0.0120	0.0140
LAG_SIZE	84,867	21.4526	21.4010	138,327	21.5100	21.4550
LAG_INFLATION	84,867	0.0298	0.0280	138,327	0.0280	0.0280
LAG_GDP	84,867	9.2078	9.2563	138,327	9.2371	9.2858

RET_SD	35,935	0.0275	0.0229	55,737	0.0265	0.0226
MOML	35,935	0.0050	0.0050	55,737	0.0081	0.0068

The table presents descriptive statistics. Panel A shows the descriptive statistics for the Fed's monetary policy surprises between 1989 and 2008, with the exception of 17th September 2001. *Total surprise* is the first principal component of daily changes in the future rates of the current month's fed funds futures, the 3-month ahead fed funds futures, and the 2-quarter, 3-quarter, and 4-quarter ahead Eurodollar futures around an FOMC meeting, multiplied by-1. *Surprise_Private info* is the fitted value of the regression of the Fed's total monetary policy surprise on the difference between the FOMC Greenbook forecasts and the private sector Blue Chip forecasts. This figure is expressed as a percentage. Panel B presents descriptive statistics for variables used in the tests. *Revision* is the first earnings forecast after an FOMC meeting minus the last earnings forecast just before an FOMC meeting, scaled by the firm's stock price prior to the revision. This figure is multiplied by 100 to express it as a percentage. *CAR* is the three-day cumulative abnormal return around the date that an analyst revises the forecast for a firm. This figure is multiplied by 100 to express it as a percentage. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *RET_SD* is firm stock return volatility prior to the forecast revision, defined as the standard deviation of a firm's daily stock returns over the past 150 days. *MOML* is the momentum in stock markets, defined as a firm's exponentially weighted (3-month half-life) cumulative return over the past 11 months. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are given in Appendix 3.1.

Table 3.3. Analyst forecast revision to the Fed's private information

	Positive Private info (Expansionary)	Negative Private info (Contractionary)	Positive Policy Surprise (Expansionary)	Negative Policy Surprise (Contractionary)
	(1)	(2)	(3)	(4)
Surprise_Private info	0.1092***	-0.1058***		
	(3.41)	(-4.73)		
Total surprise			0.0106	-0.0105
			(1.04)	(-1.22)
NFIRM	0.0028*	0.0001	0.0012	0.0029
	(1.65)	(0.10)	(1.11)	(1.63)
NIND	-0.0028	0.0031	0.0013	-0.0026
	(-0.78)	(1.31)	(0.54)	(-0.70)
BSIZE	0.0001	$-2.65*10^{-5}$	0.0001	$3.56*10^{-5}$
	(0.42)	(-0.22)	(0.51)	(0.16)
HORIZON	0.0011**	0.0010***	0.0011***	0.0008
	(2.16)	(3.13)	(3.84)	(1.10)
FEXP	-0.0002	-0.0001	-0.0004	0.0002
	(-0.31)	(-0.17)	(-0.88)	(0.28)
LAG_TACC	-0.5321**	-0.1383	-0.0609	-0.7051***
	(-2.43)	(-0.54)	(-0.26)	(-2.75)
LAG_PROFIT	3.2332***	4.9317***	4.7856***	3.6428***
	(4.11)	(5.47)	(6.02)	(4.43)
LAG_SIZE	0.1227***	0.2547***	0.2526***	0.0854**
	(3.79)	(7.99)	(9.12)	(2.12)

LAG_INFLATION	-3.8643**	-7.6673***	-2.7949	-10.0892***
	(-2.10)	(-3.61)	(-1.54)	(-3.52)
LAG_GDP	-1.7011**	-1.1826**	-2.3458***	0.8249
	(-2.07)	(-2.05)	(-5.16)	(0.66)
Intercept	11.8581*	5.0660	14.8228***	-8.8578
	(1.67)	(1.03)	(3.89)	(-0.80)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	84,867	138,327	165,265	57,929
Adj. R-square	49.4%	42.5%	40.9%	50.9%

This table presents the regression analysis of the forecast revision on the Fed's private information component of the monetary policy surprise. The *Positive Private info* column includes observations with the value of *Surprise_Private info* larger than 0. The *Negative Private info* column includes the observations with a value of *Surprise_Private info* lower than 0. The dependent variable is the analyst's forecast revision, which is the first earnings forecast after an FOMC meeting minus the last earnings forecast just before an FOMC meeting, scaled by the firm's stock price prior to the revision. This figure is multiplied by 100 to express it as a percentage. *Surprise_Private info* is the fitted value of the regression of the Fed's total monetary policy surprise on the difference between the FOMC Greenbook forecasts and the private sector Blue Chip forecasts. This figure is expressed as a percentage. *Total surprise* is a daily change in Fed's funds rate futures contracts between the FOMC announcement date and the previous trading day, and this calculated policy surprise is multiplied by -1. This figure is expressed as a percentage. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 3.1. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Table 3.4: Post-FOMC meeting disclosure change

	Positive Private info (Expansionary) (1)	Negative Private info (Contractionary) (2)
Surprise_Private info	-0.0413	0.1842*
	(-0.78)	(1.90)
Surprise_Private info*Post_1994	0.1762***	-0.2942***
	(2.61)	(-2.99)
NFIRM	0.0028	0.0001
	(1.62)	(0.08)
NIND	-0.0028	0.0031
	(-0.78)	(1.33)
BSIZE	0.0001	$-2.49*10^{-5}$
	(0.43)	(-0.21)
HORIZON	0.0010*	0.0010***
	(1.91)	(2.98)
FEXP	-0.0002	-0.0001
	(-0.27)	(-0.18)
LAG_TACC	-0.5411**	-0.1399
	(-2.46)	(-0.54)
LAG_PROFIT	3.2611***	4.9293***
	(4.14)	(5.46)
LAG_SIZE	0.1227***	0.2548***
	(3.79)	(7.99)
LAG_INFLATION	-3.8364**	-7.9388***
	(-2.09)	(-3.73)
LAG_GDP	-1.6277**	-1.0779*
	(-1.98)	(-1.86)
Intercept	11.2724	4.2161
	(1.58)	(0.86)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	84,867	138,327
Adj. R-square	49.4%	42.5%

This table presents the regression analysis of the forecast revision as a response to the Fed's private information component of the monetary policy surprise, conditional on the post-FOMC meeting disclosure mechanism. The *Positive Private info* column includes the observations with the value of *Surprise_Private info* larger than 0. The *Negative Private info* column includes the observations with the value of *Surprise_Private info* lower than 0. The dependent variable is the analyst's forecast revision, which is the first earnings forecast after an FOMC meeting minus the last earnings forecast just before an FOMC meeting, scaled by the firm's stock price prior to the revision. This figure is multiplied by 100 to express it as a percentage. *Surprise_Private info* is the fitted value of the regression of the Fed's total monetary policy surprise on the difference between the FOMC Greenbook forecasts and the private sector Blue Chip forecasts. This figure is expressed as a percentage. *Post_1994* is a dummy variable that takes the value of 1 if an observation is after 1994, 0 otherwise. *Post_1994* is omitted from the regression since it is absorbed by the year fixed-effect. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 3.1. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Table 3.5. FOMC meetings with reverse direction in monetary policy

	Positive Private info (Expansionary)	Negative Private info (Contractionary)
	(1)	(2)
Surprise_Private info	0.0983***	-0.1088***
	(2.76)	(-4.65)
Reverse direction	-0.0945	-0.2262***
	(-0.97)	(-2.80)
Surprise_Private info*Reverse direction	0.0327	-0.1991**
	(0.28)	(-2.06)
NFIRM	0.0028	0.0001
	(1.63)	(0.08)
NIND	-0.0028	0.0031
	(-0.77)	(1.30)
BSIZE	0.0001	$-3.11*10^{-5}$
	(0.44)	(-0.26)
HORIZON	0.0010**	0.0010***
	(1.96)	(3.07)
FEXP	-0.0002	-0.0001
	(-0.33)	(-0.14)
LAG_TACC	-0.5086**	-0.1363
	(-2.33)	(-0.52)
LAG_PROFIT	3.2417***	4.9323***
	(4.13)	(5.47)
LAG_SIZE	0.1236***	0.2549***
	(3.80)	(7.99)
LAG_INFLATION	-4.2697**	-6.3421***
	(-2.34)	(-2.79)
LAG_GDP	-1.6347**	-1.5359**
	(-2.00)	(-2.57)
Intercept	11.2913	8.0452
	(1.59)	(1.58)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	84,867	138,327
Adj. R-square	49.4%	42.5%

This table presents the regression analysis of the forecast revision as a response to the Fed's private information component of the monetary policy surprise, conditional on the directions of actual monetary policies. The *Positive Private info* column includes the observations with the value of *Surprise_Private info* larger than 0. The *Negative Private info* column includes the observations with the value of *Surprise_Private info* lower than 0. The dependent variable is the analyst's forecast revision, which is the first earnings forecast after an FOMC meeting minus the last earnings forecast just before an FOMC meeting, scaled by the firm's stock price prior to the revision. This figure is multiplied by 100 to express it as a percentage. *Surprise_Private info* is the fitted value of the regression of the Fed's total monetary policy surprise on the difference between the FOMC Greenbook forecasts and the private sector Blue Chip forecasts. This figure is expressed as a percentage. *Reverse direction* is a dummy variable that takes the value of 1 if the direction of the monetary policy from an FOMC meeting is opposite to previous ones, 0 otherwise. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 3.1. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Table 3.6. Analysts' task-specific experience

	Unscheduled		Non-zero	
	Positive Private info (Expansionary)	Negative Private info (Contractionary)	Positive Private info (Expansionary)	Negative Private info (Contractionary)
	(1)	(2)	(3)	(4)
Surprise_Private info	0.1546***	-0.1722***	-0.0135	-0.2475***
	(2.74)	(-4.65)	(-0.12)	(-3.36)
Specific experience	0.0190**	0.0054	0.0023	0.0002
	(2.40)	(1.12)	(0.70)	(0.12)
Surprise_Private info*Specific experience	-0.0119	0.0164**	0.0049	0.0045*
	(-1.44)	(2.33)	(1.27)	(1.75)
NFIRM	0.0037	0.0012	0.0034	0.0015
	(1.47)	(0.75)	(1.35)	(0.93)
NIND	-0.0055	0.0004	-0.0055	0.0003
	(-1.12)	(0.12)	(-1.12)	(0.10)
BSIZE	0.0001	0.0001	0.0001	0.0001
	(0.59)	(0.67)	(0.45)	(0.79)
HORIZON	-0.0000	0.0013***	0.0000	0.0012***
	(-0.04)	(2.77)	(0.05)	(3.82)
FEXP	0.0006	0.0004	0.0003	0.0006
	(0.72)	(0.61)	(0.34)	(1.05)
LAG_TACC	-0.4110	-0.2182	-0.4747*	-0.2115
	(-1.54)	(-0.82)	(-1.75)	(-1.53)

LAG_PROFIT	2.6974**	5.0275***	2.7074**	5.0210***
	(2.30)	(5.11)	(2.31)	(9.97)
LAG_SIZE	0.1896***	0.2784***	0.1899***	0.2788***
	(3.76)	(6.78)	(3.75)	(11.48)
LAG_INFLATION	-0.3884	-4.3546	0.8288	-4.0495**
	(-0.15)	(-1.54)	(0.30)	(-2.17)
LAG_GDP	-1.8357	-1.2249*	-0.3581	-1.3846***
	(-1.35)	(-1.87)	(-0.27)	(-3.19)
Intercept	11.8654	4.8074	-1.3318	6.1623
	(0.99)	(0.81)	(-0.11)	(1.61)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	35,191	66,576	35,191	66,576
Adj. R-square	52.3%	41.5%	52.3%	41.5%

This table presents the regression analysis of the forecast revision as a response to the Fed's private information component of the monetary policy surprise, conditional on the analysts' task-specific experience. The *Positive Private info* column includes the observations with the value of *Surprise_Private info* larger than 0. The *Negative Private info* column includes the observations with the value of *Surprise_Private info* lower than 0. The dependent variable is the analyst's forecast revision, which is the first earnings forecast after an FOMC meeting minus the last earnings forecast just before an FOMC meeting, scaled by the firm's stock price prior to the revision. This figure is multiplied by 100 to express it as a percentage. *Surprise_Private info* is the fitted value of the regression of the Fed's total monetary policy surprise on the difference between the FOMC Greenbook forecasts and the private sector Blue Chip forecasts. This figure is expressed as a percentage. *Specific experience* is the number of FOMC meetings an analyst has experienced from year-5 to year-1 prior to the current FOMC meeting. 2 types of FOMC meetings are considered: 1.Unscheduled FOMC meetings; 2.FOMC meetings with non-zero total monetary policy surprise. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 3.1. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by firm. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Table 3.7. Market reactions to analysts' forecast revisions

	Positive Private info (Expansionary) (1)	Negative Private info (Contractionary) (2)
Revision	0.1274***	0.2283***
	(4.63)	(3.93)
Abs_Surprise_Private info	0.2537**	0.2657
	(2.14)	(1.48)
Abs_Surprise_Private info*Revision	0.0648*	0.0359
	(1.78)	(0.45)
NFIRM	0.0010	-0.0024
	(0.16)	(-0.42)
NIND	-0.0089	0.0015
	(-0.70)	(0.13)
BSIZE	-0.0340	-0.0411
	(-0.97)	(-0.99)
HORIZON	-0.1593**	-0.1278**
	(-2.91)	(-2.14)
FEXP	-0.0044	0.0033
	(-1.33)	(1.32)
LAG_TACC	0.4575	-0.0428
	(0.71)	(-0.08)
LAG_PROFIT	4.9972***	7.9594***
	(5.24)	(3.22)
LAG_SIZE	0.0656	0.1280***
	(1.58)	(3.96)
RET_SD	20.3531***	7.8466
	(5.75)	(1.11)
MOML	-0.9423	4.4503**
	(-0.20)	(2.79)
LAG_INFLATION	-27.7946**	-13.8611
	(-2.51)	(-1.04)
LAG_GDP	5.7725	0.9837
	(0.96)	(0.24)
Intercept	-53.1260	-11.3528
	(-0.98)	(-0.30)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	35,935	55,737

Adj. R-square	0.84%	1.51%

This table presents the regression analysis of the impact of the Fed's private information on the relationship between market reaction and the analyst's forecast revision. The *Positive Private info* column includes the observations with the value of *Surprise_Private info* larger than 0. The *Negative Private info* column includes the observations with the value of *Surprise_Private info* smaller than 0. The dependent variable is the three-day cumulative abnormal return around the date that an analyst revises the forecast for a firm. This figure is multiplied by 100 to express it as a percentage. *Revision* is the analyst's forecast revision, which is the first earnings forecast after an FOMC meeting minus the last earnings forecast just before an FOMC meeting, scaled by the firm's stock price prior to the revision. This figure is multiplied by 100 to express it as a percentage. *Abs_Surprise_Private info* is the absolute value of the private information, which is the fitted value of the regression of the Fed's total monetary policy surprise on the difference between the FOMC Greenbook forecasts and the private sector Blue Chip forecasts. This figure is expressed as a percentage. *NFIRM* is the number of firms covered by an analyst. *NIND* is the number of industries covered by an analyst. *BSIZE* is the number of unique analysts employed by a brokerage house that hires this analyst. *HORIZON* is the number of days between an analyst's earnings forecast date and firm's earnings announcement date. *FEXP* is the number of quarters for which an analyst has issued at least one earnings forecast for a firm. *LAG_TACC* is lagged total accruals, defined as the firm's income before extraordinary items minus total cash flow from operations in the prior quarter, scaled by average total assets in the prior quarter. *LAG_PROFIT* is lagged annual profitability, defined as the firm's income before extraordinary items in the prior quarter, scaled by average total assets in the prior quarter. *LAG_SIZE* is lagged firm size, defined as the natural logarithm of the market value of equity in the prior quarter. *RET_SD* is firm stock return volatility prior to the forecast revision, defined as the standard deviation of a firm's daily stock returns over the past 150 days. *MOML* is the momentum in stock markets, defined as a firm's exponentially weighted (3-month half-life) cumulative return over the past 11 months. *LAG_INFLATION* is a lagged inflation rate, defined as the U.S. 12-month inflation rate in the prior month. *LAG_GDP* is lagged GDP, defined as the natural logarithm of the U.S. GDP in billions of USD in the prior quarter. All detailed variable definitions are presented in Appendix 3.1. The *t*-statistics are reported below coefficient estimates and are calculated on the basis of robust standard errors clustered by analyst-firm and year. *, **, *** indicate statistical significance (two-sided) at the 0.1, 0.05 and 0.001 levels.

Chapter 4: Thorough Analysts and Intra-Industry Information Transfer [35]

4.1. Introduction

Disclosure of firm information can affect peer firms in the same industry (e.g., Admati and Pfleiderer, 2000, Dye, 1990). As financial intermediaries, analysts play an important role in facilitating information transfer so that they further influence firms' decisions (e.g., Hilary and Shen, 2013, Guan et al., 2015, Martens and Sextroh, 2021). However, this crucial role in information transmission is influenced by their research portfolios. As documented in prior studies, having fewer research subjects (i.e., less portfolio complexity) can significantly concentrate the attention of the analysts and therefore lead to better performance (e.g., Clement, 1999, Clement and Tse, 2005). This chapter examines how thorough analysts play a role in intra-industry information transfer and the impact this has on the investments of peer firms in the context of the firm's accounting restatement.

This chapter focuses on the firm's accounting restatement to examine the impact of thorough analysts for two reasons. First, by focusing on the firm's accounting restatement, it explores the impacts of analysts' research portfolios that go beyond market effects, and which can therefore show some real effects on peer firms' investments emanating from this process of transmitting restatement information. Second, the firms' accounting restatement events are not expected by the analysts and therefore not related to the analysts' research portfolios. [36] As a comparison, the analysts can have some anticipation for some traditional firms' events, such as earnings announcements, IPOs, and change their behaviour strategically (Bourveau et al., 2022). The setting of the firm's accounting restatement might therefore provide some robust empirical evidence and complement

[35] This chapter is based on a solo author working paper "Thorough Analysts and Intra-Industry Information Transfer". The paper has been presented in the Ph.D. seminar of Lancaster university, 2018 NWSSDTP Job Market and Employability Skills Workshop, 35th EAA Doctoral Colloquium, and 1st Lancaster/TSM/WHU PhD workshop.

[36] Other firms' restatement announcements are less likely to affect peer firms' analyst portfolio complexity. To prove this point, this chapter compares mean and median analyst portfolio complexity of peer firms before and after restatement announcements and there is no significant difference (untabulated). Furthermore, this chapter conducts firm-level regression that the peer firms' analyst portfolio complexity as a function of number of accounting restatement cases announced in an industry-year and other factors related to portfolio complexity (untabulated). The variable of number of accounting restatement cases is insignificant, suggesting that announcements of other firms' restatements does not affect peer firms' analyst portfolio complexity.

previous studies which explore the association between analysts' forecasts and the complexity of their portfolios (e.g., Clement, 1999, Drake and Myers, 2011).

Analysts play a crucial role in transmitting the restatement information and thus having a further impact on peer firms' investments. On the one hand, analysts can affect peer firms' investments by increasing the monitoring of these firms. Because analysts interact with the managers and serve as external firm monitors (e.g., Jensen and Meckling, 1976, Healy and Palepu, 2001), they can constrain firms' earnings management (e.g., Yu, 2008, Irani and Oesch, 2016), scrutinize managerial behaviour (e.g., Chen et al., 2015b, Chan and Liu, 2022) and improve the quality of firms' investments (e.g., To et al., 2018).

The accounting restatements of other firms reveal important information relevant to peer firms' investments (Durnev and Mangen, 2009). Peer firms' investments might be distorted if they use restating firms' financial information to assist investment decisions (e.g., Beatty et al., 2013, Li, 2015).[37] Moreover, like restating firms, peer firms may also have the issue of tainted financial reporting (Gleason et al., 2008, Kravet and Shevlin, 2010) and this low-quality financial reporting leads to inappropriate investments (Biddle et al., 2009). Therefore, other firms' restatement announcements can cause analysts to alter their perceptions of peer firms' investments. Following other firms' restatement announcements, analysts generalize the restatement information to peer firms (Xu et al., 2006, Gleason et al., 2008), raise the alert and enhance monitoring.[38] This increased monitoring makes peer firms further revise down their investments by questioning the peer firms' distorted investments or by improving the quality of peer firms' financial reporting.

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[37] Anecdotal evidence from the WorldCom case shows that other firms in the telecommunication industry used WorldCom's inaccurate financial reporting information to value their investment projects and assisted investment decisions, and therefore made inappropriate investments (See more, Sidak, 2003).

[38] For instance, Orbital ATK, a U.S. aerospace contractor, announced on 10th August 2016 that there had been a financial misstatement. This financial misstatement is attributed to the "existence of one or more material weaknesses in its internal control over financial reporting and disclosure controls and procedures"(US Today, 10th August, 2016). Vista Outdoor Inc, a peer firm of Orbital ATK, hosted a conference call on 11th August 2016. During the call, Rommel Dionisio, an analyst from Wunderlich Securities Inc, mentioned " yesterday Orbital ATK talked about restatement of earnings due to the Lake City facility. I just want to make sure that had absolutely nothing to do with you guys" (For further detail, see, https://seekingalpha.com/article/3998824-vista-outdoors-vsto-ceo-mark-deyoung-q1-2017-results-earnings-call-transcript). Another example is the Great Atlantic & Pacific Tea Company's (A&P) $36.8 million restatement in 2002. Investors and analysts questioned whether other peer firms had similar issues and reported untrusted financial information (Gleason et al., 2008, p.85).

On the other hand, analysts can affect peer firms' investments indirectly through their effects on peer firms' investors. Analysts' forecasts and recommendations are informative for the investors (e.g., Lys and Sohn, 1990, Francis and Soffer, 1997). In response to other firms' restatements, analysts make downward revisions to their forecasts for the peer firms (Xu et al., 2006, Gleason et al., 2008). This restatement information transmitted by analysts can lower investors' perceptions of peer firms' expected future earnings and, therefore, reduce the funds available to peer firms. Ultimately, a reduction in funds makes peer firms further revise their investments (e.g., Hoshi et al., 1991, Minton and Schrand, 1999).

This chapter argues that the role of analysts in intra-industry information transfer is affected by their choice of the industries they follow. Analysts vary significantly in terms of the number of industries in their research portfolios (Kini et al., 2009) and this diversity can affect their transmission of restatement information. Analysts have limited time, and if this is not sufficient for work, their forecasts will be impaired (Pisciotta, 2021). With less complex portfolios, analysts are more thorough because they can devote more attention to the industries they follow (e.g., Clement, 1999, Drake and Myers, 2011). Moreover, to attract asset managers, analysts have an incentive to cover as many industries as possible. However, they may not have the ability or interest to deal with all the industries they follow and cannot constantly carry out high-quality research. Because of all these factors, a complex portfolio can damage the transmission of restatement information through analysts.

Although a complex portfolio can distract analysts' attention, it may also improve their performance by exposing them to different industries and allowing them to compare the prospects of one industry relative to others (Kini et al., 2009, Kadan et al., 2012). While following more industries has the potential to benefit analysts, most previous studies tend to support the idea of less complex portfolios (e.g., Clement, 1999, Clement and Tse, 2005, Drake and Myers, 2011, Jung et al., 2012). Therefore, this chapter posits that thorough analysts, who have less complex portfolios, can devote more attention to the announcement of the restatement, facilitate intra-industry information transfer and make peer firms further revise their investments after other firms' restatement announcements.

To test this prediction, this chapter uses 1169 accounting irregularity cases (i.e., intentional accounting restatement cases) from the U.S. General Accounting/Government Accountability Office (GAO) and Audit Analytics. The sample covers the period from 1998 to 2017 and includes firms in the same industries as the restating firms based on the three-digit SIC classification (i.e., peer firms). This chapter excludes restating firms and further includes firms which do not have restatements announced in their industries.

This chapter finds that peer firms followed by analysts who are more thorough (i.e., less complex portfolios measured by fewer three-digit SIC industries in their research portfolios) further reduce investments after other firms' restatement announcements. These main findings are consistent with spillover effects, which empirically have concerns about endogeneity issues (e.g., Berg et al., 2021). To alleviate concerns about possible endogeneity issues, 6 additional tests are provided. First, to mitigate the concern that the occurrence of the restatements in an industry is cyclical and clustered in certain periods, the regression is re-estimated by including industry-year fixed effects.

Second, this chapter uses a reduced sample, made up of peer firms which had at least five years' observations before their industry had its first restatement announced and dropping peer firms after their industry had its first restatement announced. This alternative empirical test based on the use of a reduced sample is not intended to claim causality. Instead, by mimicking the empirical design of the staggered difference-in-difference, to some extent, it tries to provide more robust empirical evidence.

Third, to control for time-invariant firm-specific characteristics, this chapter replaces the raw values of variables with their changes. Four, to ensure that the peer firms can fully incorporate the impact of the restatements and revise their investments, the main analyses are re-estimated by using the values of the test variables lagged for two, three, four and five years. Five, to alleviate concerns that the choice of analyst portfolio is endogenous,[39]

[39] Most previous studies regard analyst portfolio choice as an exogenous variable in empirical design (e.g., Clement, 1999, Jung et al., 2012). Furthermore, Kini et al. (2009) show that, at least for the U.S. sample, after controlling for the portfolio selection, analysts with more complex portfolios still have less forecast accuracy. This result further confirms that, although the structure of analyst portfolio might not a random choice, the inference with regard to the portfolio complexity is not significantly biased.

the regression model controls for additional variables that affect analysts' portfolio selection. Six, the peer firms' investments are likely to be affected by fraudulent cases in an industry that has inflated earnings, and above all, the analysts can transmit this inflated financial information and further influence peer firms (Beatty et al., 2013). To capture the full picture including both accounting restatement and fraudulent cases, the regression model includes an additional variable that counts the number of firms inflating their financial performance in a given industry and year. These additional tests support the inferences of the main test.

Next, this chapter examines the role of thorough analysts in intra-industry information transfer depending on the information included in the restatement cases. Restatement cases with rich information may reveal (more) information related to peer firms' investments and are likely to trigger analysts' monitoring of peer firms. Furthermore, information-rich cases cause more significant market reactions and thus are more likely to make investors change their perceptions of peer firms. The information richness of cases is associated with types of restated items. Specifically, revenues and expenses are informative since they are core account items that reflect firms' underlying activities (e.g., Palmrose and Scholz, 2004, Penman and Penman, 2007, Durnev and Mangen, 2009). If this chapter uses the number of cases that have revenues or expenses restated (i.e., core account cases) as a more refined measure of restatement information, the results are consistent with the main analyses and further support the important role of thorough analysts.

Finally, this chapter explores the channels through which analysts influence peer firms' investments. First, peer firms with a higher probability of having distorted investments are more likely to attract scrutiny from analysts and thus revise their investments following other firms' restatement announcements. Specifically, young firms, which rely more on other firms' financial information, and firms with lower accounting quality are both more likely to have distorted investments. The main analyses are re-estimated across the sample partitions with young and old firms, and firms with high and low accounting quality. Of all the sub-samples, results show that young firms and firms with low accounting quality have significant results. These results support the argument that analysts affect peer firms' investments directly through the increased monitoring of peer firms.[40]

Second, this chapter examines market reaction to analyst forecast revision. This chapter finds that peer firms' three-trading-day cumulative market-adjusted abnormal returns are positively associated with analyst forecast revision for the peer firms after other firms' restatement announcements. Moreover, the market reacts more strongly to revisions made by thorough analysts. These results show that the restatement information transmitted by analysts changes investors' perceptions of peer firms and support the argument that analysts affect peer firms' investments indirectly through the impact on peer firms' investors.

This chapter contributes to the literature in three ways. First, it extends the understanding of analysts as a mechanism for transmitting information across firms. The literature has documented that, by discovering, processing and disseminating information, analysts facilitate information transmission (e.g., Piotroski and Roulstone, 2004, Badertscher et al., 2013, Shroff et al., 2013, Guan et al., 2015, Martens and Sextroh, 2021). Specifically, by following several firms, analysts gain knowledge from disclosing firms, change their forecasts for the peer firms, and in doing this transmit information across firms (e.g., Beatty et al., 2013, Hilary and Shen, 2013). Rather than focusing on the analyst following, this chapter contributes to this strand of the literature by providing evidence that analysts' characteristics are also crucial for their information transmission.[41] More thorough analysts can facilitate better intra-industry information transfer.

Second, this chapter adds to the literature on analysts as an effective monitoring mechanism. Previous studies have used exogenous shocks and instrumental variables to develop causal links between analyst following and corporate behaviour, and show that

[40] There are other monitoring mechanisms which may affect peer firms' investments following other firms' restatement announcements. Firms with higher institutional ownership (Ferreira and Matos, 2008) and a stronger market for corporate control have lower capital expenditure (Gompers et al., 2003). Table 4.8 includes institutional ownership and the index of anti-takeover provisions. While firms with weaker anti-takeover provisions further reduce investments after other firms' restatement announcements, the inference with regard to the monitoring function of analysts does not change.

[41] In an untabulated test, Eq. (4.1) is re-estimated after adding the number of analysts following peer firms and its interaction with *Restatement*. The main inference with regard to the analyst portfolio complexity does not change after including analyst following.

analysts scrutinize managerial behaviour (Irani and Oesch, 2013, Chen et al., 2015b, Chan and Liu, 2022), reduce earnings management (e.g., Yu, 2008, Irani and Oesch, 2016), constrain aggressive disclosure of the non-GAAP (Christensen et al., 2021), and influence firms' investments (e.g., Derrien and Kecskés, 2013, To et al., 2018). Rather than exploiting unexpected changes in analyst following, this chapter shows that other firms' restatement announcements, which are unrelated to the analyst characteristics of peer firms, make analysts tighten up their scrutiny of peer firms. This increased monitoring makes peer firms further revise down their investments.

Third, it contributes to the literature on the complexity of analyst portfolios. Previous studies have shown that analysts with less complex portfolios have better forecasts (e.g., Clement, 1999, Clement and Tse, 2005, Drake and Myers, 2011). Adding to the discussion and the literature, this chapter shows that the analyst portfolio can influence the externalities of restatement information and therefore has a real effect on firms.

This chapter proceeds as follows. Section 4.2 reviews the literature and develops hypotheses. Section 4.3 outlines the data and main research design. Section 4.4 reports results and findings, and section 4.5 concludes.

4.2. Literature review and hypotheses development

4.2.1 Accounting restatement

Both the regulatory bodies and accounting standards require the firm's financial reporting to be free from errors. However, misstated accounting information is not a rare occurrence (Li, 2015). In such cases, firms have to correct the mistakes in their financial statements and announce restatements. While mistakes can be caused by minor issues such as software problems or clerical errors, there are cases of firms intentionally misreporting their accounting information (e.g., Hennes et al., 2008, Beatty et al., 2013). Moreover, depending on whether restated items are related to firms' fundamental underlying activities, cases can be categorized into core and non-core account restatements (e.g., Palmrose and Scholz, 2004, Durnev and Mangen, 2009).

Restatement announcements generally have an adverse impact on the restating firms.

Previous studies show that, following the disclosure of restatements, restating firms experience a significant reduction in their share price, and legal sanctions and litigation against their management and auditors initiated by shareholders (e.g., Palmrose and Scholz, 2004, Karpoff et al., 2007, Amiram et al., 2020). In particular, the negative impacts on the restating firms are more significant for restatement cases with the intentional purpose (Hennes et al., 2008) and relating to core earnings items (Palmrose and Scholz, 2004).

Moreover, peer firms are also affected by what is disclosed in the restatements. After a restatement announcement, peer firms reduce investments to correct decisions made on the basis of the incorrect financial information originally issued by the restating firm (Durnev and Mangen, 2009, Li, 2015). Additionally, peer firms often experience a decline in their share price because investors doubt the quality of peer firms' financial reporting (Gleason et al., 2008) or change their perceptions of the peer firms' future performance (Xu et al., 2006).

In addition to the regulatory bodies and shareholders, analysts also play an active role in restatement cases since accounting information is fundamental to their equity analysis. The literature shows that analysts seek further information if they have any doubts about firms' financial information (Brown et al., 2015), take on a whistleblower role in some restatement cases (Dyck et al., 2010), and significantly reduce forecasts for the restating firms (e.g., Griffin, 2003, Palmrose et al., 2004). Furthermore, analysts can interact and communicate with management through conference calls (e.g., Yu, 2008, Brown et al., 2015). During conference calls, the analysts may raise questions about the restatements and try to get further information from the management.[42]

4.2.2 Transmission of restatement information

Analysts play an important role in facilitating information transfer within the

[42] For example, Gymboree Corp hosted a conference call on 25th April, 2012. Carla Casella, the analyst of JP Morgan Chase & Co, asked "I have one housekeeping on the restatements. Could you please remained us what the restatement's related to? I notice you really stated sales for retail in play and music. And, also, it looks like some of your adjustments to EBIDTA were restated, where I think you [loan to] purchasing accounting adjustments in all acquisition-related." (See more, https://seekingalpha.com/symbol/GYMB?news=transcripts).

industry. They identify the common industry component of each firm's news event and disseminate this information so that it feeds into the pricing process of all the firms covered (Piotroski and Roulstone, 2004). Hilary and Shen (2013) argue that analysts learn new knowledge from firms that disclose managerial forecasts and thus improve their forecasts for non-disclosing firms. Beatty et al. (2013) show that for a sub-sample of high analyst coverage overlap between fraudulent firms and peer firms, analysts issue more favourable recommendations for peer firms during the period in which the fraudulent firms overstate their performance. They argue that analysts' recommendations could be the channel for transmitting information that is relevant to peer firms' investments. Furthermore, Martens and Sextroh (2021) show that business and technology information can be transmitted across firms through overlaps in analyst coverage.

This process of information transmission also applies to restatement information. Figure 4.1 outlines the theoretical framework for how analysts transmit the restatement information and influence peer firms. Analysts can transmit restatement information and further influence peer firms' investments directly through their monitoring function. The theoretical arguments from the literature suggest that financial analysts fulfil the role of an external monitor and, as such, affect corporate behaviour (e.g., Jensen and Meckling, 1976, Healy and Palepu, 2001).[43] Recent empirical evidence supports this analyst monitoring function. Yu (2008) shows that firms with more analysts have fewer issues of earnings management. Similarly, Irani and Oesch (2016) show that an unexpected drop in analyst following makes firms shift from real earnings management, which is relatively difficult for analysts to detect, to accrual earnings management. Furthermore, using a similar setting of an unexpected drop in analyst following, previous studies present evidence to show that analysts are crucial to scrutinizing managerial behaviour and constraining aggressive disclosure of non-GAAP earnings (Chen et al., 2015b, Christensen et al., 2021). While monitoring pressure exerted by analysts may force firms to focus on short-term performance and inhibit innovation (He and Tian, 2013), it can

[43] Jensen and Meckling (1976, p.354) argue that "monitoring activities become specialized to those institutions and individuals who possess comparative advantages in these activities. One of the groups who seem to play a large role in these activities is composed of the security analysts".

also facilitate total factor productivity and improve investment quality (To et al., 2018).

[Insert Figure 4.1]

Firms in the same industry share similar external conditions and face similar growth opportunities (Hilary and Shen, 2013). As a result, peer firms often use other firms' financial information to identify investment opportunities, value the payoff of their investment projects and make investment decisions (e.g., Bushman and Smith, 2001, Durnev and Mangen, 2009, Badertscher et al., 2013). Peer firms' investments will be distorted if they use financial information from restating firms. [44] Moreover, peer firms may have the same problems of tainted financial reporting as restating firms (Gleason et al., 2008, Kravet and Shevlin, 2010), and this sort of low-quality financial reporting leads to inappropriate investments (Biddle et al., 2009). Consequently, accounting restatements reveal a problem that firms in the same industry group have in common with the restating firms (Guo et al., 2017) and this has crucial implications for peer firms' investments (Durnev and Mangen, 2009).

As financial intermediaries, analysts observe major events within the industry and change their forecast behaviours for other firms (Ramnath, 2002, Piotroski and Roulstone, 2004). Specifically, in the wake of restatement announcements, analysts may raise the alert and start to question peer firms.[45] Both Xu et al. (2006) and Gleason et al. (2008) find that in response to the accounting restatements, analysts significantly reduce their forecasts for peer firms, indicating that other firms' restatements affect analysts' confidence in the peer firms. Additionally, analysts may express their concerns and interact with the management through firm conference calls (Yu, 2008). This additional monitoring by analysts makes peer firms correct distorted investments arising from the

[44] For instance, WorldCom inflated its net income and this distorted financial information made other telecommunication firms overvalue the investments (Sidak, 2003). The revelation of the WorldCom case had a negative impact on investments across the whole industry (Infoword, 2nd Oct, 2002), and some firms like AT&T in fact sold off related businesses (The Wall Street Journal, 26th May, 2004).

[45] Gleason et al. (2008, p.85) provide an example "Great Atlantic & Pacific Tea Company's (A&P) $36.8 million restatement in 2002…one industry analyst who said that vendor allowances are ''a very complicated area of accounting that's only now getting a lot of [investor] attention''… Two other grocery companies (Safeway and Albertson's) ''didn't immediately respond to requests for comment'', leaving investors and analysts in doubt as to whether these firms' previously reported financial results were tainted. One industry analyst predicted that other (unnamed) grocery retailers would eventually restate earnings because of improper accounting for vendor allowances."

use of financial information from restating firms, or enhances the quality of peer firms' financial reporting, and eventually enables peer firms to improve investment quality and revise distorted investments.

One could argue that, since analysts serve the role of the external monitor, they should anticipate the accounting restatement (Dyck et al., 2010) and exert pressure on peer firms even before the restatement announcement. However, this argument may not hold for two reasons. First, it is questionable to view analysts as an effective mechanism for anticipating restatements. Griffin (2003) shows that analysts only revise their forecasts for restating firms in the month or six months following the restatement announcements. Furthermore, Brown et al. (2015) present evidence to show that analysts make little effort to detect corporate misreporting.[46] Second, even if analysts can detect some early signs that a firm will make a restatement announcement, they are unlikely to generalize this unconfirmed information to peer firms and exert pressure at the risk of damaging relationships with peer firms' managers.

In addition to the direct channel, the restatement information transmitted by analysts can further affect peer firms' investments indirectly through its impact on peer firms' investors. The literature has documented that analysts' forecasts and recommendations are informative for investors (e.g., Francis and Soffer, 1997, Lys and Sohn, 1990). In particular, previous studies show that there would be negative market reactions or even disciplinary actions against management if analysts predicted a deterioration in performance and reduced forecasts (e.g., Brennan et al., 1993, Hong et al., 2000).

Following restatement announcements, analysts significantly reduce forecasts for peer firms and such forecast revision can lower investors' perceptions of peer firms' expected future earnings (Xu et al., 2006). On receiving restatement information from analysts, investors may choose to reduce investments in peer firms, and a reduction in external financing can adversely affect peer firms' investments (e.g., Hoshi et al., 1991,

[46] Brown et al. (2015, p.24) asked analysts how much attention they paid to intentional financial misrepresentation and analysts responded that "It's somebody else's job to figure out if the information they're giving us is correct. We have to take that on faith…It's up to the auditor to catch that…If they were able to fool the auditor into a clean audit opinion, I'm never going to be able to catch it just from the information that's in a Q or a K."

Minton and Schrand, 1999). Therefore, restatement information transmitted through analysts' forecasts can influence peer firms' investments by affecting investors' perceptions and funding decisions.

4.2.3 Analysts with broad versus narrow portfolios

The role of analysts in facilitating intra-industry information transfer is highly influenced by their research portfolios. Analysts have a limited amount of time and resources. Previous studies have shown that distracted analysts with insufficient time have worse forecast performance than those with sufficient time (Pisciotta, 2021). The more industries analysts follow, the more complex their research portfolios are. This complexity has a negative effect in that they can devote less attention to the individual industry as the overall number of industries they follow grows (e.g., Clement, 1999, Drake and Myers, 2011). [47] Yet the need to attract clients gives analysts an incentive to cover as many industries as possible. However, they may not have the intention or the ability to handle every industry and cannot constantly conduct high-quality research. Therefore, distracted analysts, who have complex research portfolios, will be less effective in facilitating the transmission of restatement information.

While a more complex portfolio results in distracting analysts' attention and reducing their effectiveness in collecting and processing information, it can also improve their performance by exposing them to other industries. Following different industries enables analysts to gain cross-industry expertise, which is the ability to assess the performance of an industry relative to other industries (Kadan et al., 2012). This expertise is particularly significant for analysts who follow different industries in the same supply chain and helps them gain the benefit of information complementarities (Kini et al., 2009, Guan et al., 2015). Consequently, a complex portfolio can enable analysts to better

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[47] To further illustrate this point, Thomas Bowman, who is CEO of the Association for Investment Manager and Research, stated that "when an analyst, especially in a smaller firm, is assigned two or three different industries to follow, that individual, if he were to follow or she were to follow every publicly [traded] company in each of those industries, would literally be responsible for following and giving due diligence to hundreds of companies, which is just—there is not enough hours in the day or the week or the month in order to do that" (The Watchdogs Didn't Bark: Enron and the Wall Street Analysts: Hearing before the Committee on Governmental Affairs United Stated Senate, 107th Cong, (2002)).

understand the impact of restatements, adjust their perceptions of peer firms and facilitate the transmission of restatement information.

Although following more industries has the potential to benefit analysts, most previous studies tend to support less complex portfolios. As the number of the industries they follow grows, analysts' forecasts become less accurate (Clement, 1999, Jacob et al., 1999, Clement and Tse, 2003, Kini et al., 2009), less bold (Clement and Tse, 2005), more optimistic (Drake and Myers, 2011) and get smaller market reactions to the revision (Jung et al., 2012). Thus, as shown in Figure 4.1, thorough analysts who have less complex portfolios can better facilitate the transmission of restatement information and have an incremental impact on peer firms' investments. The above discussion leads to the first hypothesis:

> **H1:** *Ceteris paribus*, peer firms further reduce their investments after other firms' restatement restatements if the peer firms are followed by thorough analysts with less complex portfolios.

The discussion suggests that thorough analysts can facilitate the transmission of restatement information and influence peer firms' investments directly through their monitoring function or indirectly through their impact on peer firms' investors. Two further hypotheses aim to explore these two channels. First, if the peer firms' investments are influenced through the direct channel, the role of analyst portfolio complexity should be (more) significant for firms with a higher probability of having distorted investments. These firms are more likely to attract scrutiny from analysts and therefore, to further revise their investments after other firms' restatement announcements.

Second, if the impact on peer firms' investments is through the indirect channel, the investors of peer firms should react to the restatement information transmitted by analysts and especially by thorough analysts. Since analysts' forecasts are informative for the investors, the market should react to analyst forecast revision for peer firms after other firms' restatement announcements. The above discussion leads to a second pair of hypotheses:

> **H2a:** *Ceteris paribus*, the role of analyst portfolio complexity in facilitating the transmission of restatement information should be (more) significant for firms which

are more likely to have distorted investments.

H2b: There is a positive association between analyst forecast revision for peer firms after other firms' restatement announcements and peer firms' cumulative abnormal return around the revision dates.

4.3. Data and research design

Table 4.1 shows the process for selecting accounting restatement cases and the sample used for the main test. Since this chapter focuses on information transmission by analysts and its incremental impact on peer firms, restatement cases that are likely to have information related to peer firms' investments are selected. Specifically, this chapter focuses only on cases of accounting irregularity (i.e., intentional accounting restatement cases). Although minor errors in the application of accounting rules and the preparation of financial reports can trigger restatements, they are less likely to be questioned by the market (Burks, 2011). By contrast, the nature of intentional restatements, i.e., firms strategically manipulating their financial reporting, makes accounting irregularity cases more likely to reveal information that is relevant to peer firms' investments and causes analysts to alter their perceptions of peer firms. What is more, market reactions to accounting irregularity cases are more significant and negative than accounting errors (Hennes et al., 2008), and are thus more likely to attract attention from both analysts and investors.

While Audit analytics identifies restatement cases primarily on the basis of 8-K 4.02 non-reliance disclosure, which has been mandated since August 2004,[48] GAO's dataset has good coverage of restatement cases from 1997 to 2005. In line with previous studies (e.g., Badertscher et al., 2011, Hennes et al., 2014), the research sample combines GAO's dataset with Audit analytics. The initial sample includes all restatement cases from GAO's dataset that are classified by Hennes et al. (2008) as an accounting irregularities in the period from 1997 to 2005. Hennes et al. (2008) regard a restatement case as accounting

[48] Before 2004, Audit analytics relied on other SEC filings such as 10-K, 10-Q, 20-F, 40-F etc to identify restatement cases (See more, https://www.auditanalytics.com/doc/dd-restatements.pdf). There are some concerns that the ability to identify the restatement cases might have been weak before 2004 (Hennes et al., 2008, Karpoff et al., 2017).

irregularity if the firm uses “fraud” or “irregularity” to describe the restatement or if there is an SEC or Department of Justice investigation, or if there is an independent (non-SEC) investigation into the restatement.

Next, the sample is extended by applying a similar definition to select cases of accounting irregularity from Audit analytics covering the period from 2006 to 2016. Restatement cases are selected if they involve fraud or irregularity, or if investigations were initiated by the SEC or other regulatory bodies. Since the typical investment model is not suitable for financial and utility firms, restatement cases that are announced by financial firms (SIC codes 6000-6999) and utility firms (SIC codes 4900-4999) are excluded. After dropping restating firms for which no industry information is given, the final restatement sample includes 1169 accounting irregularity cases.

The sample of the main tests covers the period from 1998 to 2017. This sample excludes firms with accounting restatements and includes the peers of the restating firms. Following Beatty et al. (2013), peers are defined as those firms with the same three-digit SIC codes as the restating firms. Additionally, those firms that do not have accounting restatements announced in their industries during the sample period are included. Moreover, financial and utility firms are removed from the sample. Finally, firms with insufficient data are excluded, yielding a final sample of 24660 firm-year observations in the main test. This chapter uses firm-level financial accounting data from Compustat, data on analysts from I/B/E/S, data to calculate abnormal returns from CRSP, firm anti-takeover index from Gompers et al. (2003) and institutional ownership information from Thomson Reuters.

[Insert Table 4.1]

The main prediction is based on the argument that analysts transmit restatement information and further affect peer firms’ investments following other firms’ restatement announcements. To test H1, this chapter estimates the following equation with the firm indexed as *i,* the year as *t* and the industry as *j*:

$$\begin{aligned} Investment_{i,t} = {} & \alpha_0 + \alpha_1 Restatement_{j,t-1} + \alpha_2 Portfolio\ complexity_{i,t-1} \\ & + \alpha_3 Restatement_{j,t-1} * Portfolio\ complexity_{i,t-1} \\ & + Control\ variables_{i,t-1} + Industry\ dummies + Year\ dummies \\ & + \varepsilon_{i,t} \end{aligned} \tag{4.1}$$

Where *Investment* is the firm's capital expenditure scaled by lagged total assets. *Restatement* is the number of accounting restatement cases announced in an industry-year. *Portfolio complexity* is the average number of industries followed by a peer firm's analysts and multiplied by -1. Detailed variable definitions are included in Appendix 4.1. Eq. (4.1) is estimated by using OLS regression and standard errors are clustered by firm.

Previous studies use the level of investments to explore the impacts of fraudulent reporting or accounting restatements on peer firms (e.g., Beatty et al., 2013, Li, 2015). Hence, this chapter also uses the level of investments to explore the impacts of accounting restatements on peer firms. Specifically, this chapter measures a peer firm's investment (*Investment*) by using capital expenditure scaled by lagged total assets. To capture the restatement information, this chapter uses the number of accounting restatement cases announced in an industry-year (*Restatement*). To measure analyst portfolio complexity, following previous studies (e.g., Drake and Myers, 2011), the average number of industries followed by a peer firm's analysts (based on three-digit SIC codes) is counted. To assist the interpretation, this mean figure is multiplied by -1 (*Portfolio complexity*). Therefore, a higher value of *Portfolio complexity* indicates that peer firms' analysts are more thorough, suggesting that they have less complex portfolios. The coefficient of interest in Eq. (4.1) is the α_3, which captures the incremental impact of other firms' restatements on peer firms' investments related to analysts with different levels of portfolio complexity. Based on H1, α_3 is expected to be negative and significant.

In addition to the measures of restatement information and portfolio complexity, a series of control variables that may affect the firms' investments are included. Previous studies find that firms' investments are influenced by financial resources, including external financing (Durnev and Mangen, 2009), firm leverage (e.g., Badertscher et al., 2013, Beatty et al., 2013) and cash flow (Li, 2015). Following these studies, the regression model controls for firms' external financing (*External financing*), leverage (*Leverage*) and cash flow from operations (*Cash*).

Additionally, the firms' investments might be driven by potential investment opportunities. Following previous studies, this chapter measures firms' investment opportunities using Tobin's Q (*Tobin Q*) (e.g., Badertscher et al., 2013, Li, 2015). Furthermore, firms' investments might be influenced by their competitive positions, so the regression model controls for peer firms' competitive positions in the industry (*Market leader*). Finally, the regression model controls for the impacts of firms' performances (*ROA*) and sizes (*Size*) on investments.

4.4. Results

4.4.1. Descriptive statistics

Table 4.2 presents summary statistics for the sample from 1998 to 2017. Capital expenditure (*Investment*) accounts for 6.5% of total assets on average. The average number of accounting restatement cases announced in an industry-year is 2.021 (*Restatement*). Turning to the measure of portfolio complexity, the average number of industries followed by a peer firm's analysts is 6.204. As for control variables, on average, the leverage and cash flow from operations account for 25.7% and 1.0% of total assets, respectively. The mean of *External financing* is 0.490. The mean of *Tobin Q* is 2.395, which is close to previous studies (e.g., Badertscher et al., 2013, Li, 2015). The average *Size* and *ROA* of firms are 6.145 and -0.089, respectively.

[Insert Table 4.2]

4.4.2. Main results

Table 4.3 column 1 shows the results of Eq. (4.1). The coefficient on *Restatement* is negative and significant (coef:-0.112, t-stat=-3.91), indicating that peer firms reduce investments following other firms' restatement announcements. This result is consistent with the conclusion of previous studies (Durnev and Mangen, 2009, Li, 2015) that peer firms reduce investments as a response to other firms' restatements. The main interest variable, the coefficient on interaction term between *Restatement* and *Portfolio* *complexity* is negative and significant (coef:-0.012, t-stat=-2.86), indicating that peer firms followed by thorough analysts further reduce investments after other firms' restatement announcements.[49] This result supports H1 and is consistent with the findings of previous studies that analysts' ability to carry out their jobs is determined by their portfolio complexity (e.g., Clement, 1999, Drake and Myers, 2011). In terms of economic significance, conditional on peer firms reducing investments following other firms' restatement announcements and if they are followed by analysts with one less industry, the investments are then further reduced by 10.71%.

[Insert Table 4.3]

The above findings are consistent with spillover effects in the context of financial information (e.g., Beatty et al., 2013, Li, 2015). However, as indicated by previous studies, the identification of spillover effects is subject to endogeneity concerns (e.g., Berg et al., 2021). To alleviate any possible concerns of endogeneity and better examine the role of thorough analyst in facilitating information transmission, this section includes 6 additional tests. First, accounting restatements may cluster at certain periods. Wang et al. (2010) show that the instances of corporate fraud are cyclical and the propensity to commit fraud increases with investors' prospects of the business condition of the industry. Restatements might therefore correlate with the industry cycle. To ensure that the main test results are not confounded by the industry cycle, in Table 4.3 column 2, the regression is re-estimated after including industry-year fixed effects. The results are similar to those reported in Table 4.3 column 1.

Second, Table 4.3 column 3 uses a reduced sample which peer firms have at least five years' observations (non-restatement period) before the first restatement is announced in their industry and excludes peer firms after the first restatement is announced in their industry. The empirical test of using this reduced sample tries to mimic the staggered difference-in-difference setting by including a non-restatement period. Though this alternative empirical test does not claim causality, it could provide further robust evidence. After changing the sample composition in this way, the coefficient on

[49] In an untabulated test, the regression is re-estimated only using observations that the value of *Restatement* is non-zero and results are still hold.

interaction term between *Restatement* and *Portfolio complexity* is negative and significant (coef:-0.067, t-stat=-1.75). These results further support the main test results.

Third, to ensure the main results are not confounded by time-invariant firm-specific characteristics, the raw values of the variables in Eq. (4.1) are replaced with change specifications:

$$\begin{aligned}\Delta Investment_{i,t-1\text{ to }t+1} &= \beta_0 + \beta_1 \Delta Restatement_{j,t-1\text{ to }t} + \beta_2 \Delta Portfolio\ complexity_{i,t-1\text{ to }t} \\ &+ \beta_3 \Delta Restatement_{j,t-1\text{ to }t} * \Delta Portfolio\ complexity_{i,t-1\text{ to }t} \\ &+ \Delta Control\ variables_{i,t-1\text{ to }t} + Industry\ dummies \\ &+ Year\ dummies + \varepsilon_{i,t} \qquad (4.2)\end{aligned}$$

Where Δ*Investment* is the percentage change in the firm's capital expenditure from t-1 to t+1. Δ*Restatement* is the change in the number of accounting restatement cases announced in an industry from t-1 to t. Δ*Portfolio complexity* is the change in the average number of industries followed by a peer firm's analysts from t-1 to t and multiplied by minus one. Δ*Control variables* are changes in the values of control variables as defined in Eq. (4.1) from t-1 to t. Eq. (4.2) is estimated by using OLS regression and standard errors are clustered by firm.

Table 4.3 column 4 reports the results of Eq. (4.2). The coefficient on the interaction between Δ*Restatement* and Δ*Portfolio complexity* is negative and significant (coef:-0.014, t-stat=-1.83), indicating that peer firms followed by analysts with less complex portfolios further reduce investment growth rate after other firms' restatement announcements. This result further supports the main result in column 1.

Four, the revisions of the investments might not be flexible and peer firms may need more than one year to fully incorporate the impact of other firms' restatements (Durnev and Mangen, 2009, Li, 2015). In such cases, the main test results cannot reflect the full impacts. Since determining precisely how long peer firms need to revise their investments is difficult, in Table 4.4, Eq. (4.1) is re-estimated with the values of the test variables lagged for two, three, four and five years. The results show that, except for column 2, the coefficients on interaction terms between *Restatement* and *Portfolio complexity* are negative and significant. These results further support the results of the main analyses.

[Insert Table 4.4]

Five, although most previous studies treat portfolio complexity as an exogenous analyst characteristic (e.g., Clement, 1999, Drake and Myers, 2011, Jung et al., 2012), analyst portfolio choice is likely to be co-determined by analysts and brokerage houses (Kini et al., 2009). Industry and firm size affect analyst portfolio choice through revenue generation for the brokerage houses. Additionally, information complementarities across different industries reduce the costs of more complex research portfolios for analysts. Moreover, the size of the brokerage house may be crucial for analyst portfolio choice and can either foster industry specialization or diversification. Finally, analysts' preferences in relation to portfolio choice may vary over their careers.

To ensure that the main test results are not biased because of the omitted analyst portfolio selection variables, the main test is re-estimated after additionally controlling for the market value of the industry (*Industry MV*), the correlation between an industry's equal-weighted stock return and the mean of other industries' equal-weighted stock returns (*Industry correlation*), brokerage house size (*Brokerage size*), and analysts' general experience (*General experience*).[50] Moreover, previous studies show that general experience and brokerage house size can significantly affect analysts' performance (e.g., Clement, 1999, Clement and Tse, 2005). Therefore, the regression model further includes interaction terms between *Restatement* and these two variables. As shown in Table 4.5, the interaction term between *Restatement* and *Portfolio complexity* is negative and significant (Column 1: coef:-0.012, t-stat=-2.77; Column 2: coef:-0.018, t-stat=-3.81), suggesting that the main test results are not biased by analyst portfolio selection. This result is consistent with Kini et al. (2009) that after controlling for analyst portfolio selection, the greater complexity of portfolios resulting from sector diversification reduces analyst forecast accuracy in the U.S. context.

[Insert Table 4.5]

Six, prior studies show that when a larger number of analysts follow fraudulent firms

[50] The untabulated regression results show that while larger brokerage houses and, larger firms and industries are associated with less complex portfolios, general experience and industry correlation have opposite effects.

it makes peer firms increase their investments during the misstatement periods (Beatty et al., 2013, Li, 2015). However, whether analysts with less complex portfolios are deceived by restating firms and are transmitting inflated financial information is still an open question. To capture the full picture of the inflated financial information and accounting restatement, a variable that counts the number of firms inflating their financial performances in an industry-year (*Misstatement*) is included in Eq.(4.1):

$$\begin{aligned} Investment_{i,t} = \eta_0 &+ \eta_1 Restatement_{j,t-1} + \eta_2 Portfolio\ complexity_{i,t-1} \\ &+ \eta_3 Restatement_{j,t-1} * Portfolio\ complexity_{i,t-1} \\ &+ \eta_4 Misstatement_{j,t-1} + \eta_5 Misstatement_{j,t-1} \\ &* Portfolio\ complexity_{i,t-1} + Control\ variables_{i,t-1} \\ &+ Industry\ dummies + Year\ dummies + \varepsilon_{i,t} \end{aligned} \tag{4.3}$$

Where *Misstatement* is the number of firms inflating their financial performances in an industry-year. The other variables are the same as Eq. (4.1). Detailed variable definitions are included in Appendix 4.1. Eq. (4.3) is estimated by using OLS regression and standard errors are clustered by firm.

Table 4.6 presents the results of Eq. (4.3). Column 1 presents some evidence that analysts with less complex portfolios transmit inflated financial information in the misstatement periods (interaction term between *Misstatement* and *Portfolio complexity*: coef:0.009, t-stat=2.03) (Beatty et al., 2013, Li, 2015). However, the inclusion of *Misstatement* does not change the inference with regard to the role of analyst portfolio complexity.

[Insert Table 4.6]

4.4.3. The information richness of accounting restatements

The role of analyst portfolio complexity in intra-industry information transfer might be affected by information included in restatement cases. Specifically, cases with rich information are more likely to have (more) information related to peer firms' investments and thus attract scrutiny from analysts. Moreover, information-rich restatement cases may lead to greater market reactions and make investors change their perceptions of peer firms. As a result, the role of analyst portfolio complexity may vary with the information included in each accounting restatement case.

The level of information included in accounting restatement cases might be affected by the restated items. The GAO's dataset reports the items restated by each firm. Figure 4.2 shows the number of accounting restatement cases with certain restated items. Of these, revenue and costs or expenses are the two most frequently restated items. More importantly, revenue and costs or expenses are core accounts that reflect firms' underlying activities (e.g., Penman and Penman, 2007, Durnev and Mangen, 2009). As a result, cases in which core account items (i.e., revenue or costs/expenses) are restated are more likely to disclose information that is related to peer firms' investments (e.g., Guilding, 1999, Guilding et al., 2000). This rich information emphasizes the role of analyst portfolio complexity in facilitating intra-industry information transfer. Hence, the number of core account cases announced in an industry-year is a more refined measure of the restatement information.

[Insert Figure 4.2]

To test the role of analyst portfolio complexity in core account restatement cases, this chapter estimates the following equation:

$$\begin{aligned} Investment_{i,t} = {} & \zeta_0 + \zeta_1 Core\ account\ cases_{j,t-1} + \zeta_2 Portfolio\ complexity_{i,t-1} \\ & + \zeta_3 Core\ account\ cases_{j,t-1} * Portfolio\ complexity_{i,t-1} \\ & + Control\ variables_{i,t-1} + Industry\ dummies + Year\ dummies \\ & + \varepsilon_{i,t} \end{aligned} \tag{4.4}$$

Where *Core account cases* is the number of accounting restatement cases that restate revenue or costs/expenses announced in an industry-year. The other variables are the same as in Eq. (4.1). Detailed variable definitions are included in Appendix 4.1. Eq. (4.4) is estimated by using OLS regression and standard errors are clustered by firm.

Eq. (4.4) replaces *Restatement* with the number of core account cases (*Core account cases*). A higher value suggests that industries have more core account cases announced. As shown in Table 4.2, the mean of *Core account cases* is 1.570, indicating that the occurrence of core account cases is not rare. Table 4.7 presents the regression results using Eq. (4.4). As shown in Table 4.7, the interaction term between *Core account cases* and *Portfolio complexity* is negative and significant (Column 1:coef:-0.018, t-stat=-3.18;

Column 2:coef:-0.015, t-stat=-2.30). This result is consistent with the main inference in Table 4.3 and further supports H1.

[Insert Table 4.7]

4.4.4. Channels through which analysts influence peer firms' investments

This section examines the possible channels through which analysts may transmit restatement information and influence peer firms' investments. As predicted by H2a, one possible way in which this may occur is that following other firms' restatement announcements, analysts increase their monitoring of peer firms, and especially of peer firms with a higher probability of having distorted investments. To examine this direct monitoring channel, the sample is divided on the basis of firms' deviation from expected investments. Following Biddle et al. (2009), the deviations from expected investments are measured as residual from a firm-level regression that investment is a function of growth opportunities:

$$Investment_{i,t} = \gamma_0 + \gamma_1 Sales\ growth_{i,t-1} + \varepsilon_{i,t} \quad (4.5)$$

Where *Investment* is a firm's capital expenditure scaled by lagged total assets in year *t*. *Sale growth* is the percentage change in a firm's sales. Eq.(4.5) is estimated for each industry-year based on two-digit SIC and for industries with at least 20 observations in a year.

To measure the distortion of investments, the firm-year observations are classified on the basis of their deviation from the expected investments. Specifically, observations in the bottom quartile (top quartile) are regarded as under-investment (over-investment).[51] In addition to the analysts, there are other monitoring mechanisms that may make peer firms revise investments following other firms' restatement announcements. Institutional investors can monitor the managers and reduce firms' capital expenditure (Ferreira and Matos, 2008). To control for the monitoring function of the institutional investors, the percentage of shares owned by the institutional investors (*Institutional Ownership*) is

[51] The maximum value of deviation from expected investments for observations of under-investments is -0.03 and the minimal value of deviation from expected investments for observations of over-investment is 0.02. Hence, firms in the under-investment (over-investment) group do indeed invest less (more) than expected.

included in the model.

Moreover, the market for corporate control can also serve as an external monitoring mechanism and improve the quality of corporate investment (Jensen, 1986). Consistent with this argument, firms with weaker anti-takeover protection have a higher firm value, fewer acquisition activities and lower capital expenditure (Gompers et al., 2003). Therefore, the anti-takeover protection index (G-index) from Gompers et al. (2003) is used as a proxy of the market for corporate control.

To extrapolate the sample of the G-index, following Biddle et al. (2009), observations with a missing G-index are set to 0 and an indicator variable that takes the value of 1 if the G-score is missing, 0 otherwise (*G-score indicator*) is included in the model. Furthermore, the G-index is multiplied by -1 to assist interpretation (*InvG-score*), so higher values of *InvG-score* suggest that firms have stricter monitoring. The regression model includes interaction terms between *Restatement* and proxies of these alternative monitoring mechanisms to capture their impacts on firms' investments separately. Therefore, to examine the direct channel, the following equations is estimated:

$$\begin{aligned} Investment_{i,t} = {} & \delta_0 + \delta_1 Restatement_{j,t-1} + \delta_2 Portfolio\ complexity_{i,t-1} \\ & + \delta_3 Restatement_{j,t-1} * Portfolio\ complexity_{i,t-1} \\ & + \delta_4 InvGscore_{i,t-1} + \delta_5 Restatement_{j,t-1} * InvGscore_{i,t-1} \\ & + \delta_6 Gscore\ indicator_{i,t-1} + \delta_7 Institutional\ Ownership_{i,t-1} \\ & + \delta_8 Restatement_{j,t-1} * Institutional\ Ownership_{i,t-1} \\ & + Control\ variables_{i,t-1} + Industry\ dummies + Year\ dummies \\ & + \varepsilon_{i,t} \qquad (4.6) \end{aligned}$$

Where *InvG-score* is the anti-takeover protection index, for which the missing value is set to 0 and multiplied by -1. *G-score indicator* is a dummy variable that takes the value of 1 if the anti-takeover protection index is missing, and 0 otherwise. *Institutional Ownership* is the percentage of shares of a firm owned by institutional investors. The other variables are the same as Eq. (4.1). Detailed variable definitions are included in Appendix 4.1. Eq. (4.6) is estimated by using OLS regression and standard errors are clustered by firm.

Table 4.8 column 1 presents the results of Eq. (4.6) and shows that the coefficient on interaction term between *Restatement* and *Portfolio complexity* is negative and significant (coef:-0.013, t-stat=-2.67), indicating that inferences with regard to the monitoring function of analysts do not change after including other monitoring mechanisms. Additionally, the coefficient on interaction term between *Restatement* and *InvG-score* is negative and significant (coef:-0.009, t-stat=-2.60), suggesting that firms with better markets for corporate control further reduce investments following other firms' restatement announcements. This result is consistent with the market for corporate control serving as an effective firm monitor (e.g., Gompers et al., 2003, Qiu and Yu, 2009).

Consistent with the prediction, Table 4.8 column 3 shows that the interaction term between *Restatement* and *Portfolio complexity* is negative and significant for peer firms with over-investment (coef:-0.034, t-stat=-1.78).[52] This result supports H2a and is consistent with the monitoring function of analysts.

Furthermore, this direct monitoring channel should be more significant for two types of firms. First, firms in their early stages are less able to make thorough decisions and are more likely to use restating firms' information and thus have distorted investments. Second, firms may have poor accounting quality, which leads to distorted investments. To further differentiate, Eq. (4.6) is re-estimated across the sample partitions with old versus young firms, and firms with high versus low accounting quality. Firm age is measured as the number of years which have elapsed since the firm first appeared on the CRSP. Following Gleason et al. (2008), the quality of accounting is measured by using the absolute value of industry-adjusted total accruals and higher value to indicate that firms have lower accounting quality.

Consistent with predictions, as shown in Table 4.8 columns 5 and 7, the coefficients on interaction term between *Restatement* and *Portfolio complexity* are negative and significant for young firms and firms with large industry-adjusted accrual (Young: coef:-0.016, t-stat=-1.93; Large: coef:-0.016, t-stat=-2.92). These results are consistent with the

[52] In untabulated test, Eq. (4.6) is re-estimated using the sample which has deviations from the expected investments neither in bottom quartile nor top quartile (i.e. peer firms only have minor deviations from expected investments). The interaction term between *Restatement* and *Portfolio complexity* is not significant. This result further confirms that analysts increase monitoring only if peer firms have sufficiently large inappropriate investments.

direct channel through which analysts increase the monitoring of peer firms and make peer firms revise their investments following other firms' restatement announcements.

[Insert Table 4.8]

H2b predicts that analysts may transmit restatement information and influence peer firms' investments through an indirect channel that changes investors' perceptions of peer firms. To explore this indirect channel, this section examines the market reaction to analyst k's forecast revisions for peer firms after other firms' restatement announcements using the following equation:

$$\begin{aligned} Cumulative\ abnormal\ return_i &= \theta_0 + \theta_1 Forecast\ revision_{i,k} + \theta_2 Low\ portfolio\ complexity_k \\ &+ \theta_3 Forecast\ revision_{i,k} * Low\ portfolio\ complexity_k \\ &+ Control\ variables_i + Industry\ dummies + Year\ dummies \\ &+ \varepsilon_{i,t} \qquad (4.7) \end{aligned}$$

Where *Cumulative abnormal return* is the three-trading-day cumulative market-adjusted abnormal return around analysts' forecast revision dates. *Forecast revision* is the difference between the first earnings per share forecast for the peer firm after other firms' restatement announcement and the last earnings per share forecast for the peer firm before other firms' restatement announcement, scaled by stock price two days before the revision date. The first forecast (last forecast) needs to be made no more than 60 days after other firms' restatement announcement (before other firms' restatement announcement). *Low portfolio complexity* is a dummy variable that takes the value of 1 if the number of industries followed by an analyst is below the sample median, and 0 otherwise. *Control variables* include Market-to-book ratio (*MB*), *Z-score*, peer firms' market value (*Log market value*) and indicator of peer firms' performances (*Loss*). Detailed variable definitions are included in Appendix 4.1. Eq. (4.7) is estimated by using OLS regression and standard errors are clustered by analyst.

The GAO's dataset searches the first date on which the restatement is publicly available in the press or other media and regards this as the revelation date. Compared with Audit Analytics regarding the filing date as the revelation date, the GAO's date is more accurate. Karpoff et al. (2017) show that the median number of days between the real initial revelation date of the restatement case and GAO's revelation date (Audit Analytics' revelation date) is 6 (44). This late revelation date in Audit Analytics is not a significant issue for the main test since the restatement affects the following year's investments. However, to alleviate the bias arising from the late revelation date in the analysis of the market reaction to the forecast revision, this section uses only restatement cases from GAO's dataset.

Table 4.2 shows that both *Cumulative abnormal return* and *Forecast revision* are negative, suggesting that restatement information has a spillover effect on peer firms (Gleason et al., 2008). Table 4.9 presents the regression results of the association between the three-trading-day cumulative market-adjusted abnormal return around revision dates and analysts' forecast revision for the peer firms after other firms' restatement announcements. The coefficients on *Forecast revision* in both columns are positive and significant (Column 1: coef:0.147, t-stat=10.33; Column 2: coef:0.133, t-stat=9.44), suggesting that investors react to analysts' forecast revisions after other firms' restatement announcements. This result is consistent with H2b and supports the indirect channel through which restatement information from analysts changes investors' perceptions of peer firms. Furthermore, the coefficient on interaction term between *Forecast revision* and *Low portfolio complexity* is positive and significant (Column 1: coef:0.051, t-stat=2.02; Column 2: coef:0.045, t-stat=1.79), indicating that investors react more strongly to forecast revisions made by more thorough analysts.

[Insert Table 4.9]

4.5. Conclusion

This chapter examines the role of thorough analysts in facilitating intra-industry information transfer in the context of the firm's accounting restatements. The accounting restatements of other firms reveal information related to peer firms' investments. As external firm monitors, analysts gain insights from other firms' restatement announcements and therefore increase the monitoring of peer firms and make peer firms further revise their investments. Furthermore, information transmitted from analysts can be indirectly used by investors to change their perceptions of peer firms and eventually make peer firms further revise their investments. This transmission of restatement information through analysts depends on the complexity of their portfolios.

Consistent with the predictions, this chapter finds that peer firms followed by thorough analysts who have less complex portfolios, further reduce investments after other firms' restatement announcements. This key finding is borne out in robustness tests and in the examination of core account cases. To explore the channel through which analysts influence peer firms' investments, the sample is split on the basis of the firms' age and accounting quality. This chapter finds that the main test results are driven by young firms and firms with poor accounting quality, all of which have a higher probability of having distorted investments. These results support the argument that thorough analysts influence peer firms' investments directly by increasing monitoring.

This chapter also finds that the market has a significant reaction to thorough analysts' forecast revision for the peer firms after other firms' restatement announcements. This result suggests that thorough analysts change investors' perceptions of peer firms and supports the argument that analysts influence peer firms' investment indirectly through their impacts on peer firms' investors. Overall, the findings of this chapter show that thorough analysts can better facilitate intra-industry information transfer.

This chapter recognizes the limitations of this research setting and empirical findings. First, the current empirical evidence is mainly based on the peer firms' investments. However, it fails to show the analysts' detailed behaviour in this process of restatement information transmission. Further empirical analysis at the analyst level is considered to enrich the findings and show direct evidence. Second, though additional tests have been implemented to alleviate the possible issue of endogeneity emanating from this accounting restatement setting, it may not be sufficient to some extent and more sophisticated analysis might be considered.

Appendix 4.1. Variable definitions

Variable	Variable description	Data source
Investment	Firm's capital expenditure scaled by lagged total assets.	Compustat
Restatement	Number of accounting restatement cases announced in an industry that a firm operates in a year.	Hennes et al, (2008) and Audit analytics
Portfolio complexity	Average number of three-digit SIC industries followed by a firm's analysts in a year and multiplied by -1.	I/B/E/S
Core account cases	Number of core account cases announced in an industry that a firm operates in a year. The core account cases are that restated items are revenue or costs/expenses.	GAO database
External financing	Firm's sum of equity issues and debt issues scaled by total assets. The equity issue is changes in book equity minus changes in retained earnings, and the debt issue is changes in assets minus changes in book equity.	Compustat
ROA	Firm's net income scaled by lagged total assets.	Compustat
Leverage	Firm's debt in current liabilities plus long-term debt scaled by lagged total assets.	Compustat
Cash	Firm's cash flow from operations scaled by lagged total assets.	Compustat
Tobin Q	Firm's total assets plus the market value of equity minus the book value of equity, all scaled by total assets.	Compustat
Market leader	A dummy variable that takes the value of 1 if a firm's market share is greater than the industry median (based on two-digit SIC) in a year, 0 otherwise.	Compustat
Size	Firm's log of total assets (in million).	Compustat
Industry MV	Log of the sum of all the firms' market values in the industry that a firm operates.	Compustat
Industry correlation	Correlation between equal-weighted stock returns of all the firms in the industry that a firm operates in and mean of equal-weighted stock returns of all the firms in other industries.	CRSP
General experience	Average number of years to the date analysts of a firm issued a forecast.	I/B/E/S

Appendix 4.1. Variable definitions (continued)

Variable	Definition	Data source
Brokerage size	Average number of analysts that a brokerage house of a firm hired.	I/B/E/S
Misstatement	Number of firms inflating their financial performance in an industry that a firm operates in a year.	Audit analytics
InvG-score	Firm's anti-takeover protection index from Gompers et al. (2003). This index is set to 0 if firms have missing value, and multiplied by -1.	Gompers et al (2003)
G-score indicator	A dummy variable that takes the value of 1 if a firm's anti-takeover protection index is missing, and 0 otherwise.	N/A
Institutional ownership	Percentage of a firm's shares owned by institutional investors.	Thomson Reuters
Firm age	Number of years since a firm was first included in CRSP.	CRSP
Industry-adj total accruals	Absolute value of industry-adjusted total accruals. The industry-adjusted total accruals is a firm's total accruals scaled by average total assets minus sample means for all the firms in the same industry. The total accruals are income before extraordinary items minus cash flow from operation.	Compustat
Cumulative abnormal return	Three-trading-day cumulative market-adjusted abnormal return around the analysts' one-year-ahead earnings per share forecast revision date.	CRSP
Forecast revision	Difference between the first earnings per share forecast for a firm after other firms' restatement announcements and the last earnings per share forecast for a firm before other firms' restatement announcements, scaled by the end-of-day share price two days before the revision. The first forecast (last forecast) needs to be made no more than 60 days after other firms' restatement announcements (before other firms' restatement announcements).	I/B/E/S
MB	Market-to-book ratio, which is the market value of a firm's equity divided by the book value of equity.	Compustat

Appendix 4.1. Variable definitions (continued)

Variable	Definition	Data source
Z-score	Altman's Z-score, which is measured as: 1.2*net working capital scaled by total assets+1.4*retained earnings scaled by total assets+3.3*earnings before interest and taxes scaled by total assets+0.6*market value of equity scaled by the book value of liabilities+1.0*sale scaled by total assets.	Compustat
Log market value	Log of a firm's market value.	Compustat
Loss	A dummy variable that takes the value of 1 if a firm makes a loss, 0 otherwise.	Compustat

Figure 4.1. Theoretical framework

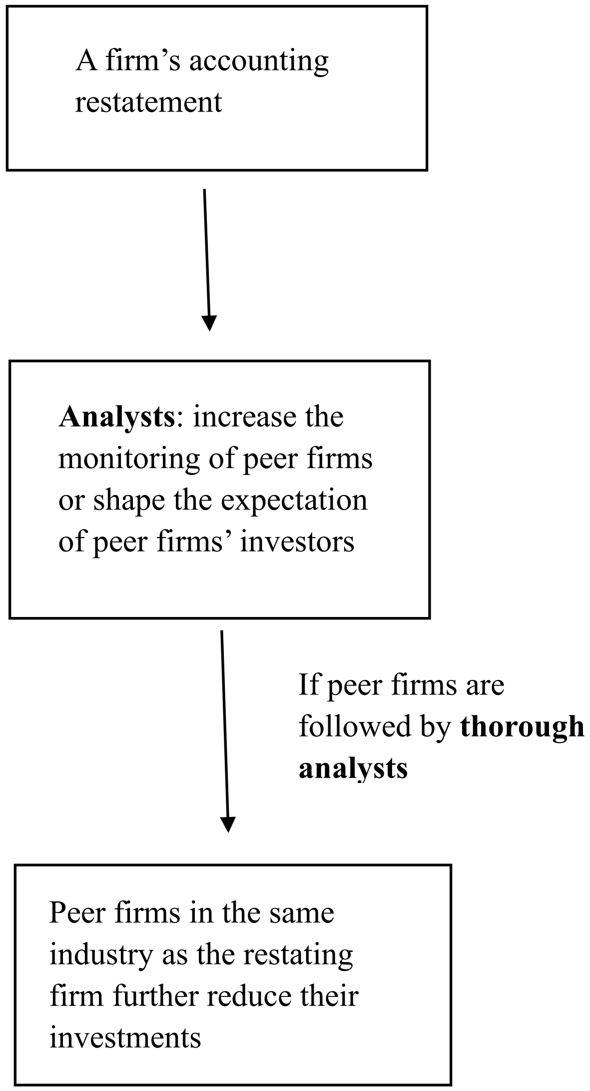
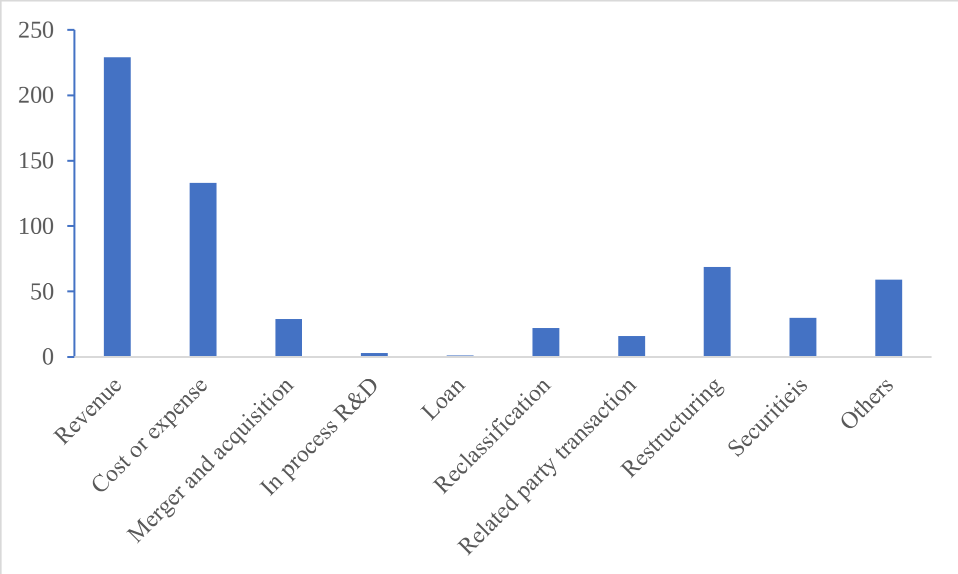


Figure 4.2. Restated items in accounting restatement cases



This figure shows the number of accounting restatement cases with certain restated items. The sample includes accounting irregularity cases identified by the GAO and classified by Hennes et al. (2008) from 1997 to 2005.

Table 4.1. Accounting restatement cases and sample selection process
Panel A. The selection of accounting restatement case

Initial accounting restatement cases from GAO over the period 1997 to 2005	2,443
Accounting irregularity cases	**652**
Initial accounting restatement cases from Audit analytics over the period 2006 to 2016	10,997
Accounting irregularity cases	**808**
Total accounting irregularity cases	**1,460**
Less	
Missing industry information	(104)
Accounting restatement cases announced by financial firms (SIC codes 6000-6999) and utility firms (SIC codes 4900-4999)	(187)
Final restatement sample	**1,169**

This table presents the selection process for accounting restatement cases. The initial sample includes all the restatement cases from GAO's dataset that are classified by Hennes et al. (2008) as accounting irregularities and covers the period from 1997 to 2005. Hennes et al. (2008) regard a restatement case as an accounting irregularity if the firm uses "fraud" or "irregularity" to describe the restatement, or if there is an SEC or Department of Justice investigation, or if there is a (non-SEC) independent investigation into the restatement. Next, the sample is extended by applying a similar definition to select accounting irregularity cases from Audit analytics covering the period from 2006 to 2016. The restatement cases are selected if they involved fraud or irregularity, or if an investigation was initiated by the SEC or other regulatory bodies. Finally, restatement cases with missing industry information and announced by financial firms or utility firms are excluded.

Panel B. Sample selection

Initial sample from Compustat during 1998-2017	193,560
Less	
Observations of firms that announce restatements	(74,355)
Observations from financial (SIC code 6000-69999) and utility industries (SIC code 4900-4999)	(49,501)
Observations of firms which are neither peers nor have no restatements announced in their industries over the sample period	(4,736)
Observations with missing data for variables	(40,308)
Final sample	24,660

This table presents the sample selection process.

Table 4.2. Descriptive statistics

Variables	N	Mean	25th	Median	75th	Std. Dev.
Test variables						
Investment	24,660	0.065	0.017	0.036	0.075	0.093
Restatement	24,660	2.021	0.000	1.000	2.000	3.577
Portfolio complexity	24,660	-6.204	-8.200	-5.600	-3.667	3.374
Misstatement	24,660	2.866	1.000	1.000	3.000	3.794
Core account cases	12,062	1.570	0.000	0.000	1.000	3.330
Cumulative abnormal return	42,617	-0.016	-0.063	-0.006	0.043	0.115
Forecast revision	42,617	-0.007	-0.004	0.000	0.003	0.092
Low portfolio complexity	42,617	0.391	0.000	0.000	1.000	0.488
Control variables						
External financing	24,660	0.490	-0.013	0.061	0.259	2.412
Leverage	24,660	0.257	0.007	0.168	0.363	0.427
Cash	24,660	0.010	-0.008	0.084	0.153	0.425
Tobin Q	24,660	2.395	1.186	1.687	2.697	2.589
Market leader	24,660	0.649	0.000	1.000	1.000	0.477
ROA	24,660	-0.089	-0.086	0.035	0.093	0.709
Size	24,660	6.145	4.591	5.880	7.501	2.114
Industry MV	23,520	11.506	9.731	11.710	13.515	2.181
Industry correlation	23,520	0.733	0.636	0.804	0.881	0.212
General experience	23,520	5.575	3.750	5.333	7.056	2.702
Brokerage size	23,520	117.382	37.750	92.333	158.000	106.853
InvG-score	12,721	-1.937	0.000	0.000	0.000	3.855
G-score indicator	12,721	0.781	1.000	1.000	1.000	0.413
Institutional ownership	12,721	0.456	0.223	0.446	0.681	0.268
MB	42,617	4.419	1.811	3.010	5.111	5.283
Z-score	42,617	6.944	2.254	4.768	9.182	9.309
Log market value	42,617	7.244	5.711	6.972	8.497	2.190
Loss	42,617	0.370	0.000	0.000	1.000	0.483
Partition variables						
Expected investment	11,569	0.004	-0.034	-0.014	0.018	0.083
Firm age	12,196	15.638	6.000	11.000	19.000	13.228
Industry-adj total accruals	12,721	0.619	0.068	0.168	0.378	1.889

This table presents summary statistics for the variables used in the multivariate analyses.

Detailed definitions of all the variables are included in Appendix 4.1. *Investment* is capital expenditure scaled by lagged total assets. *Restatement* is the number of accounting restatement cases announced in an industry-year. *Portfolio complexity* is the average number of three-digit SIC industries followed by the analysts of a firm and multiplied by minus one. *Misstatement* is the number of firms that inflate their financial performances in an industry-year. *Core account cases* is the number of accounting restatement cases that restates revenue or costs/expenses announced in an industry-year. *Cumulative abnormal return* is the three-trading-day cumulative market-adjusted abnormal return around the forecast revision date. *Forecast revision* is the difference between the first earnings per share forecast for the peer firm after other firms' restatement announcements and the last earnings per share forecast for the peer firm before other firms' restatement announcements, scaled by the end-of-day share price two days before the revision. *Low portfolio complexity* is a dummy variable that takes the value of 1 if the number of industries followed by an analyst is lower than the sample median, and 0 otherwise. *External financing* is the sum of equity issues and debt issues scaled by lagged total assets. *Leverage* is debt in current liabilities plus long-term debt scaled by lagged total assets. *Cash* is cash flow from operations scaled by lagged total assets. *Tobin Q* is total assets plus the market value of equity minus the book value of equity, all scaled by total assets. *Market leader* is a dummy variable that takes the value of 1 if a firm's market share is greater than the industry median, and 0 otherwise. *ROA* is net income scaled by lagged total assets. *Size* is a log of total assets. *Industry MV* is the log of the sum of the market values of all the firms in an industry. *Industry correlation* is the correlation between the equal-weighted stock returns of all the firms in an industry and the mean of the equal-weighted stock returns of all the firms in other industries. *General experience* is the average number of years to date for which analysts of a firm have issued a forecast. *Brokerage size* is the average number of analysts hired by the brokerage houses of a firm. *InvG-score* is the firm anti-takeover protection index from Gompers et al. (2003). This index is set to 0 if firms have missing values, and multiplied by minus one. *G-score indicator* is a dummy variable that takes the value of 1 if a firm's anti-takeover protection index is missing, and 0 otherwise. *Institutional Ownership* is the percentage of shares owned by institutional investors. *MB* is the market-to-book ratio. *Z-score* is Altman's Z-score. *Log market value* is the log of a firm's market value. *Loss* is a dummy variable that takes the value of 1 if a firm makes a loss, and 0 otherwise. *Expected investment* is the deviation from the expected investment, which is the residual of regression that firm's investment is a function of the lagged sale growth rate. *Firm age* is the number of years to the date since a firm was first included in CRSP. *Industry-adj total accrual* is the absolute value of industry-adjusted total accruals. The industry-adjusted total accruals are the firm's total accruals scaled by average total assets minus sample means for all the firms in the same industry. All variables are winsorized at the 1 percent and 99 percent level.

Table 4.3. Peer firms' investments after other firms' restatement announcements

	Predicted sign	(1)	(2)	(3)	(4)
		Main tests		Reduced sample	Change
Restatement	-	-0.112***		-0.288	-0.009
		(-3.91)		(-1.38)	(-0.85)
Restatement*Portfolio complexity	-	-0.012***	-0.014***	-0.067*	-0.014*
		(-2.86)	(-2.89)	(-1.75)	(-1.83)
Portfolio complexity		0.129***	0.141***	0.191***	-0.000
		(5.42)	(5.29)	(4.34)	(-0.04)
External financing		0.278***	0.232***	0.693**	-0.074**
		(4.57)	(3.92)	(2.32)	(-2.03)
Leverage		0.759**	0.728*	-0.842	0.065
		(2.07)	(1.84)	(-0.99)	(0.32)
Cash		2.364***	2.346***	1.609**	0.016
		(6.42)	(6.04)	(2.45)	(0.07)
Tobin Q		0.497***	0.472***	0.348***	0.098***
		(10.42)	(9.39)	(3.05)	(5.10)
Market leader		0.084	0.098	0.288	-0.094
		(0.47)	(0.50)	(0.68)	(-1.09)
ROA		-0.033	-0.215	1.515*	0.112
		(-0.13)	(-0.78)	(1.88)	(0.55)
Size		-0.260***	-0.238***	-0.431***	2.621***
		(-3.98)	(-3.27)	(-3.15)	(16.07)
Intercept		6.011***	7.170***	4.466	0.350***
		(11.39)	(14.83)	(0.91)	(4.13)
Observations		24,660	24,660	4,075	19,249
Adjusted R-squared		0.34	0.35	0.36	0.10
Industry fixed effects		Yes	No	Yes	Yes
Year fixed effects		Yes	No	Yes	Yes
Industry-year fixed effects		No	Yes	No	No

This table presents OLS regression analyses of peer firms' investments after other firms' restatement announcements conditional on the analysts' portfolio complexity of peer firms. Detailed definitions of all the variables are included in Appendix 4.1. Columns 1, 2 and 4 include peers of the restating firms from accounting restatement cases identified by GAO and Audit analytics, and firms in industries that do not have restatements announced. Column 3 includes the peer firms that had at least five years' observations before their industry had its first restatement announced, and excludes peer firms after their industry had its first restatement announced. The dependent variable in Columns 1, 2 and 3 is *Investment*, which is capital expenditure scaled by lagged total assets and expressed as a percentage. *Restatement* is the number of accounting restatement cases announced in an industry-year. *Portfolio complexity* is the average number of three-digit SIC industries followed by the analysts of a firm and multiplied by minus one. *External financing* is the sum of the equity issues and debt issues scaled by lagged total assets. *Leverage* is debt in current liabilities plus long-term debt scaled by lagged total assets. *Cash* is cash flow from operations scaled by lagged total assets. *Tobin Q* is total assets plus the market value of equity minus the book value of equity, all scaled by total assets. *Market leader* is a dummy variable that takes the value of 1 if a firm's market share is greater than the industry median, and 0 otherwise. *ROA* is net income scaled by lagged total assets. *Size* is the log of total assets. All independent variables are lagged. Column 4 uses change specifications. The dependent variable in Column 4 is the percentage change in *Investment* from *t-1* to *t+1*. The independent variables are changes in the values of *Restatement*, *Portfolio complexity*, *External financing*, *Leverage*, *Cash*, *Tobin's Q*, *Market leader, ROA* and *Size* from *t-1* to *t*. The *t*-statistics are based on standard errors clustered by firm and reported in parentheses. ***,**,* significant at 1%, 5% and 10% levels.

Table 4.4. Test variables lagged for different years

	Predicted sign	(1)	(2)	(3)	(4)
		2 years lag	3 years lag	4 years lag	5 years lag
Restatement	-	-0.132***	-0.109***	-0.084***	-0.060**
		(-4.61)	(-2.99)	(-2.80)	(-2.03)
Restatement*Portfolio complexity	-	-0.012**	-0.012	-0.012**	-0.011**
		(-2.49)	(-1.47)	(-2.25)	(-2.12)
Portfolio complexity		0.106***	0.034	0.064***	0.057***
		(4.77)	(1.48)	(3.05)	(2.67)
External financing		0.773***	1.012***	0.796***	0.663***
		(4.75)	(5.96)	(4.38)	(5.32)
Leverage		0.569	-0.293	-0.372	-0.334
		(1.30)	(-0.85)	(-1.13)	(-1.16)
Cash		3.874***	3.900***	3.524***	3.763***
		(7.09)	(7.07)	(6.02)	(5.96)
Tobin Q		0.541***	0.441***	0.440***	0.356***
		(11.44)	(8.00)	(8.57)	(7.84)
Market leader		0.098	0.219	0.150	0.072
		(0.56)	(1.23)	(0.80)	(0.37)
ROA		1.169***	0.639*	0.610	0.585
		(2.83)	(1.66)	(1.40)	(1.34)
Size		-0.287***	-0.191***	-0.162***	-0.143**
		(-4.53)	(-3.14)	(-2.61)	(-2.30)
Intercept		6.055***	5.191***	4.990***	5.006***
		(11.88)	(10.67)	(10.06)	(9.59)
Observations		23,100	21,243	19,524	17,035
Adjusted R-squared		0.36	0.37	0.36	0.37
Industry fixed effects		Yes	Yes	Yes	Yes
Year fixed effects		Yes	Yes	Yes	Yes

This table presents OLS regression analyses of the role of analysts' portfolio complexity using the values of the test variables (i.e., *Restatement* and *Portfolio complexity*) lagged for two, three, four and five years. Detailed definitions of all the variables are included in Appendix 4.1. The sample includes peers of the restating firms from accounting restatement cases identified by GAO and Audit analytics, and firms in industries that do not have restatements announced. The dependent variable is *Investment*, which is capital expenditure scaled by lagged total assets and expressed as a percentage. *Restatement* is the number of accounting restatement cases announced in an industry-year. *Portfolio complexity* is the average number of three-digit SIC industries followed by the analysts of a firm and multiplied by minus one. *External financing* is the sum of the equity issues and debt issues scaled by lagged total assets. *Leverage* is debt in current liabilities plus long-term debt scaled by lagged total assets. *Cash* is cash flow from operations scaled by lagged total assets. *Tobin Q* is total assets plus the market value of equity minus the book value of equity, all scaled by total assets. *Market leader* is a dummy variable that takes the value of 1 if a firm's market share is greater than the industry median, and 0 otherwise. *ROA* is net income scaled by lagged total assets. *Size* is the log of total assets. The *t*-statistics are based on standard errors clustered by firm and reported in parentheses. ***,**,* significant at 1%, 5% and 10% levels.

Table 4.5. Analyst portfolio selection

	Predicted sign	(1)	(2)
Restatement	-	-0.108***	-0.224***
		(-3.66)	(-5.33)
Restatement*Portfolio complexity	-	-0.012***	-0.018***
		(-2.77)	(-3.81)
Portfolio complexity		0.116***	0.126***
		(4.57)	(4.91)
External financing		0.284***	0.282***
		(4.32)	(4.29)
Leverage		0.603*	0.621*
		(1.65)	(1.70)
Cash		2.670***	2.656***
		(6.96)	(6.95)
Tobin Q		0.479***	0.478***
		(9.63)	(9.64)
Market leader		0.111	0.121
		(0.60)	(0.65)
ROA		-0.065	-0.059
		(-0.24)	(-0.22)
Size		-0.260***	-0.268***
		(-3.84)	(-3.95)
Industry MV		0.850***	0.839***
		(5.08)	(5.01)
Industry correlation		0.155	0.168
		(0.37)	(0.40)
General experience		-0.072***	-0.078***
		(-3.07)	(-2.96)
*Restatement*General experience*			0.004
			(0.72)
Brokerage size		-0.001	-0.002**
		(-0.65)	(-2.16)
*Restatement*Brokerage size*			0.001***
			(4.79)
Intercept		-6.839***	-6.475***
		(-4.92)	(-4.64)
Observations		23,520	23,520
Adjusted R-squared		0.35	0.35
Industry fixed effects		Yes	Yes
Year fixed effects		Yes	Yes

This table presents OLS regression analyses of the role of analysts' portfolio complexity after including analysts' portfolio selection variables. Detailed definitions of all the variables are included in Appendix 4.1. The sample includes peers of the restating firms from accounting restatement cases identified by GAO and Audit analytics, and firms in industries that do not have restatements announced. The dependent variable is *Investment*, which is capital expenditure scaled by lagged total assets and expressed as a percentage. *Restatement* is the number of accounting restatement cases announced in an industry-year. *Portfolio complexity* is the average number of three-digit SIC industries followed by the analysts of a firm and multiplied by minus one. *External financing* is the sum of the equity issues and debt issues scaled by lagged total assets. *Leverage* is debt in current liabilities plus long-term debt scaled by lagged total assets. *Cash* is cash flow from operations scaled by lagged total assets. *Tobin Q* is total assets plus the market value of equity minus the book value of equity, all scaled by total assets. *Market leader* is a dummy variable that takes the value of 1 if a firm's market share is greater than the industry median, and 0 otherwise. *ROA* is net income scaled by lagged total assets. *Size* is the log of total assets. *Industry MV* is the log of the sum of the market values of all the firms in an industry. *Industry correlation* is the correlation between the equal-weighted stock returns of all the firms in an industry and the mean of the equal-weighted stock returns of all the firms in other industries. *General experience* is the average number of years to date for which analysts of a firm have issued a forecast. *Brokerage size* is the average number of analysts hired by brokerage houses of a firm. All independent variables are lagged. The *t*-statistics are based on standard errors clustered by firm and reported in parentheses. ***,**,* significant at 1%, 5% and 10% levels.

Table 4.6. Misstatement periods

	Predicted sign	(1)	(2)
Restatement	-	-0.137***	
		(-4.47)	
Restatement*Portfolio complexity	-	-0.018***	-0.018***
		(-3.55)	(-3.08)
Portfolio complexity		0.115***	0.131***
		(4.62)	(4.72)
Misstatement	+	0.038	
		(1.50)	
Misstatement*Portfolio complexity	+	0.009**	0.007
		(2.03)	(1.28)
External financing		0.279***	0.232***
		(4.56)	(3.92)
Leverage		0.760**	0.728*
		(2.08)	(1.84)
Cash		2.363***	2.345***
		(6.42)	(6.04)
Tobin Q		0.497***	0.472***
		(10.41)	(9.39)
Market leader		0.085	0.098
		(0.48)	(0.50)
ROA		-0.030	-0.213
		(-0.12)	(-0.77)
Size		-0.261***	-0.239***
		(-3.99)	(-3.28)
Intercept		5.950***	7.172***
		(11.27)	(14.83)
Observations		24,660	24,660
Adjusted R-squared		0.34	0.35
Industry fixed effects		Yes	No
Year fixed effects		Yes	No
Industry-year fixed effects		No	Yes

This table presents OLS regression analyses of the role of analysts' portfolio complexity after including misstatement periods. Detailed definitions of all the variables are included in Appendix 4.1. The sample includes peers of restating firms from accounting restatement cases identified by GAO and Audit analytics, and firms in industries that do not have restatements announced. The dependent variable is *Investment*, which is capital expenditure scaled by lagged total assets and expressed as a percentage. *Restatement* is the number of accounting restatement cases announced in an industry-year. *Misstatement* is the number of firms that inflate their financial performances in an industry-year.

Portfolio complexity is the average number of three-digit SIC industries followed by the analysts of a firm and multiplied by minus one. *External financing* is the sum of the equity issues and debt issues scaled by lagged total assets. *Leverage* is debt in current liabilities plus long-term debt scaled by lagged total assets. *Cash* is cash flow from operations scaled by lagged total assets. *Tobin Q* is total assets plus the market value of equity minus the book value of equity, all scaled by total assets. *Market leader* is a dummy variable that takes the value of 1 if a firm's market share is greater than the industry median, and 0 otherwise. *ROA* is net income scaled by lagged total assets. *Size* is the log of total assets. All independent variables are lagged. The *t*-statistics are based on standard errors clustered by firm and reported in parentheses. ***,**,* significant at 1%, 5% and 10% levels.

Table 4.7. Core account cases

	Predicted sign	(1)	(2)
Core account cases	-	-0.081*	
		(-1.82)	
Core account cases*Portfolio complexity	-	-0.018***	-0.015**
		(-3.18)	(-2.30)
Portfolio complexity		0.102***	0.102***
		(3.33)	(3.00)
External financing		0.155**	0.114
		(2.20)	(1.61)
Leverage		1.152**	1.138*
		(2.13)	(1.96)
Cash		2.131***	2.131***
		(3.98)	(3.83)
Tobin Q		0.530***	0.506***
		(8.56)	(7.91)
Market leader		0.068	0.022
		(0.28)	(0.09)
ROA		-0.271	-0.420
		(-0.77)	(-1.10)
Size		-0.251***	-0.232***
		(-3.01)	(-2.62)
Intercept		6.507***	7.236***
		(10.61)	(12.95)
Observations		12,062	12,062
Adjusted R-squared		0.31	0.33
Industry fixed effects		Yes	No
Year fixed effects		Yes	No
Industry-year fixed effects		No	Yes

This table presents OLS regression analyses of the role of analysts' portfolio complexity using core account cases. Detailed definitions of all the variables are included in Appendix 4.1. The sample includes peers of restating firms from core account cases identified by GAO, and firms in industries that do not have restatements announced. The dependent variable is *Investment*, which is capital expenditure scaled by lagged total assets and expressed as a percentage. *Core account cases* is the number of cases that restate revenue or costs/expenses announced in an industry-year. *Portfolio complexity* is the average number of three-digit SIC industries followed by the analysts of a firm and multiplied by minus one. *External financing* is the sum of the equity issues and debt issues scaled by lagged total assets. *Leverage* is debt in current liabilities plus long-term debt scaled by lagged total assets. *Cash* is cash flow from operations scaled by lagged total assets. *Tobin Q* is total assets plus the market value of equity minus the book value of equity, all scaled by total assets. *Market leader* is a dummy variable that takes the value of 1 if a firm's market share is greater than the industry median, and 0 otherwise. *ROA* is net income scaled by lagged total assets. *Size* is the log of total assets. All independent variables are lagged. The *t*-statistics are based on standard errors clustered by firm and reported in parentheses. ***,**,* significant at 1%, 5% and 10% levels.

Table 4.8. The analyst as external monitor

	Predicted sign		Expected investment		Firm age		Industry-adj total accruals	
			Under	Over	Old	Young	Small	Large
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Restatement	-	-0.069	-0.101	-0.184	-0.139*	0.084	0.098	-0.174***
		(-1.37)	(-1.15)	(-1.08)	(-1.82)	(1.06)	(0.78)	(-3.03)
Restatement*Portfolio complexity	-	-0.013***	-0.012	-0.034*	-0.009	-0.016*	-0.004	-0.016***
		(-2.67)	(-1.51)	(-1.78)	(-1.28)	(-1.93)	(-0.36)	(-2.92)
Portfolio complexity		0.096***	0.052	0.248***	0.119***	0.047	0.095**	0.068
		(2.89)	(0.92)	(2.60)	(3.14)	(0.76)	(2.20)	(1.44)
InvG-score		0.054	0.169	0.190	0.021	-0.047	0.091	0.006
		(0.70)	(1.46)	(1.30)	(0.23)	(-0.24)	(0.78)	(0.10)
*Restatement*InvG-score*	-	-0.009***	-0.014**	-0.011	-0.009**	-0.010	0.007	-0.012***
		(-2.60)	(-1.99)	(-0.92)	(-2.00)	(-1.44)	(0.43)	(-3.30)
G-score indicator		0.315	-0.472	-0.535	0.740	1.396	-0.271	0.893
		(0.45)	(-0.53)	(-0.41)	(0.90)	(0.95)	(-0.25)	(1.45)
Institutional Ownership		1.718***	0.907	1.961	0.394	3.039***	2.307***	0.821
		(3.14)	(1.21)	(1.44)	(0.51)	(3.55)	(2.77)	(1.34)
*Restatement*Institutional Ownership*	-	-0.014	0.047	0.123	0.095	-0.165*	0.036	0.038
		(-0.21)	(0.47)	(0.63)	(1.01)	(-1.71)	(0.19)	(0.58)
External financing		0.190***	0.322	-0.143	0.430**	0.051	0.122	0.279***
		(2.81)	(1.32)	(-1.13)	(2.46)	(0.64)	(0.96)	(3.37)
Leverage		0.901*	-0.252	1.092	-0.355	1.351**	0.787	1.174**

	(1.81)	(-0.36)	(1.00)	(-0.60)	(2.12)	(1.21)	(2.20)
Cash	1.965***	2.655***	3.667***	8.309***	0.909*	1.625**	2.821***
	(4.05)	(3.04)	(3.60)	(6.62)	(1.78)	(2.37)	(4.22)
Tobin Q	0.508***	0.413***	0.585***	0.514***	0.534***	0.607***	0.423***
	(8.87)	(4.11)	(7.21)	(5.27)	(7.04)	(6.18)	(6.64)
Market leader	0.312	0.064	0.036	-0.001	0.311	0.290	0.267
	(1.28)	(0.21)	(0.06)	(-0.00)	(0.93)	(0.79)	(1.00)
ROA	-0.187	0.627	-1.548	-1.364*	-0.146	-0.125	-0.563
	(-0.59)	(0.86)	(-1.59)	(-1.78)	(-0.47)	(-0.23)	(-1.49)
Size	-0.349***	-0.476***	-0.675**	-0.376***	-0.141	-0.489***	-0.232**
	(-3.19)	(-3.36)	(-2.29)	(-2.73)	(-0.74)	(-2.94)	(-2.33)
Intercept	5.460***	6.421***	15.736***	6.451***	2.157	7.235***	3.633***
	(5.71)	(4.92)	(6.73)	(5.57)	(1.08)	(5.14)	(3.74)
Observations	12,721	2,906	2,881	6,240	5,956	6,376	6,345
Adjusted R-squared	0.37	0.43	0.38	0.46	0.34	0.39	0.31
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents OLS regression analyses of the role of analyst portfolio complexity across the sample partition on the basis of the probability of having distorted investments. Detailed definitions of all the variables are included in Appendix 4.1. The sample includes peers of restating firms from accounting restatement cases identified by GAO and Audit analytics, and firms in industries that do not have restatements announced. Columns 2 and 3 present the results of groups of firms with under or over-investment. A firm has under (over) investment if its deviation from the expected investment is in the bottom quartile (top quartile). The deviation from the expected investment is residual of regression that firm's investment is a function of lagged sales growth rate. Columns 4 and 5 present the results of groups of old and young firms. A firm is old (young) if its age is above (below) the sample median. The age of a firm is the number of years to the date since a firm was first included in CRSP. Columns 6 and 7 present the results of groups of firms with small and large absolute values of industry-adjusted total accruals. A firm has large (small) industry-adjusted total accruals if its absolute value of industry-adjusted total accruals is above (below) the sample median. The industry-adjusted total accruals are the firm's total accruals scaled by average total assets minus sample means for all the firms in the same industry. The dependent variable is *Investment*, which is capital expenditure scaled by lagged total assets and expressed as a percentage. *Restatement* is the number of accounting restatement cases announced in an industry-year. *Portfolio complexity* is the average number of three-digit SIC industries followed by the analysts of a firm and multiplied by minus one. *InvG-score* is the firms' anti-takeover protection index from Gompers et al. (2003). This index is set to 0 if firms have missing values, and multiplied by minus one. *G-score indicator* is a dummy variable that takes the value of 1 if a firm's anti-takeover protection index is missing, and 0 otherwise. *Institutional Ownership* is the percentage of shares owned by institutional investors. *External financing* is the sum of the equity issues and debt issues scaled by lagged total assets. *Leverage* is debt in current liabilities plus long-term debt scaled by lagged total assets. *Cash* is cash flow from operations scaled by lagged total assets. *Tobin Q* is total assets plus the market value of equity minus the book value of equity, all scaled by total assets. *Market leader* is a dummy variable that takes the value of 1 if a firm's market share is greater than the industry median, and 0 otherwise. *ROA* is net income scaled by lagged total assets. *Size* is the log of total assets. All independent variables are lagged. The *t*-statistics are based on standard errors clustered by firm and reported in parentheses. ***,**,* significant at 1%, 5% and 10% levels.

Table 4.9. Market reaction to analyst forecast revision

	Predicted sign	(1)	(2)
Forecast revision	+	0.147***	0.133***
		(10.33)	(9.44)
Low portfolio complexity*Forecast revision	+	0.051**	0.045*
		(2.02)	(1.79)
Low portfolio complexity		-0.001	-0.003**
		(-0.87)	(-2.06)
MB			0.000
			(0.10)
Z-score			0.001***
			(8.50)
Log market value			0.002***
			(3.87)
Loss			-0.019***
			(-8.85)
Intercept		-0.002	-0.016***
		(-0.88)	(-3.98)
Observations		42,617	42,617
Adjusted R-squared		0.036	0.052
Industry fixed effects		Yes	Yes
Year fixed effects		Yes	Yes

This table reports the OLS regression analyses of the market reaction to an analyst's one-year-ahead earnings per share forecast revision for the peer firms after other firms' restatement announcements. Detailed definitions of all the variables are included in Appendix 4.1. The sample includes peers of restating firms from accounting restatement cases identified by the GAO. The dependent variable is *Cumulative abnormal return*, which is the three-trading-day cumulative market-adjusted abnormal return around the forecast revision date. *Forecast revision* is the difference between the first earnings per share forecast for the peer firm after other firms' restatement announcements and the last earnings per share forecast for the peer firm before other firms' restatement announcements, scaled by the end-of-day share price two days before the revision. *Low portfolio complexity* is a dummy variable that takes the value of 1 if the number of industries followed by an analyst is lower than the sample median, and 0 otherwise. *MB* is the market-to-book ratio. *Z-score* is Altman's Z-score. *Log market value* is the log of a firm's market value. *Loss* is a dummy variable that takes the value of 1 if a firm makes a loss, and 0 otherwise. The *t*-statistics are based on standard errors clustered by analyst and reported in parentheses. ***,**,* significant at 1%, 5% and 10% levels.

Chapter 5: Conclusion

This thesis focuses on the interaction between sell-side financial analysts, the central bank and the external information environment. Specifically, this thesis explores how central bank monetary policy influences analysts' forecasts, how the private information embedded in central bank monetary policy further shapes analysts' expectations and therefore affects their forecasts, and the impact of the analysts' dedication to industries on transmitting accounting restatement information across firms. As this thesis explores the research topics across several different disciplines, I draw upon theories and employ empirical analysis from accounting, finance and economics.

This thesis includes three related yet self-contained studies. Chapter 2 of this thesis investigates the impact of the central bank's monetary policy surprises on analysts' short-term earnings forecasts. Though expectation management is important to the central bank, it is difficult in practice, leading to a monetary policy surprise. This monetary policy surprise is likely to bias analysts' earnings forecasts if the analysts are irrational in processing macroeconomic information. This chapter shows that the Fed's monetary policy surprises make analysts produce biased forecasts. Furthermore, the results show that the improved post-FOMC meeting disclosure is ineffective in alleviating analysts' biased forecasts. As well as that, firms with poor reporting quality drive the results of biased forecasts.

Chapter 2 contributes to the literature in three ways. First, it contributes to the literature on central bank. Instead of focusing on macroeconomic indicators, general financial market or firms, this chapter focuses on the impact of monetary policy surprises on analysts. Second, this chapter extends the understanding of the association between macroeconomic factors and analysts' forecast performance, and contributes to the literature on the interaction between macro-level and micro-level entities. Third, this chapter adds to the analyst literature on how analysts use different sources of information to formulate forecasts.

Chapter 3 of this thesis explores how analysts interpret and incorporate the central bank's private information. By accessing other sources of information and employing different models, the central bank holds private information, which is relevant to market participants and can update market expectations. As for the interpretation of the central bank's private information, the literature provides mixed theoretical predictions. The results of this chapter show that analysts follow conventional theories of monetary policy transmission (theories of information effects) to interpret expansionary (contractionary) monetary policy revealed by the Fed's private information and revise their forecasts. Furthermore, analysts with task-specific experience from past FOMC meetings support the interpretation following conventional theories of monetary transmission. The results of market reaction to analysts' forecast revision in the light of the Fed's private information confirm the role of analysts in transmitting central bank monetary policy.

Chapter 3 contributes to the literature in three ways. First, by examining the impact of the Fed's private information on updating analysts' forecasts, it contributes to the literature on the central bank's disclosure of private information and its associated effects. Second, it responds to the call for understanding the heterogeneity in the transmission of monetary policy and adds to the previous studies which explore the interaction between the central bank, financial market and firms. Third, it extends the understanding of the association between analysts' experience and their forecasts.

Chapter 4 of this thesis examines how analysts' research portfolio choices affect the transmission of restatement information across firms. By processing and disseminating value-relevant information, analysts can transmit restatement information within the same industry and therefore further shape peer firms' investment decisions. This information transmission is affected by the complexity of analysts' portfolios. The results of this chapter show that peer firms followed by more thorough analysts (i.e., less complex research portfolio) further reduce their investments after other firms' restatement announcements. Further explorations show that the reduction in peer firms' investments is made because thorough analysts fulfil the role of external firm monitor and change investors' perceptions of peer firms.

Chapter 4 contributes to the literature in three ways. First, it adds to the literature on information disclosure by extending the understanding of analysts as a crucial mechanism for transmitting information across firms. Second, it contributes to the literature on analysts as an effective monitoring mechanism. By contrast to previous studies of exploiting unexpected changes in analyst following, this chapter shows that other firms' restatement announcements, which are unrelated to analyst characteristics of peer firms, make analysts tighten up the scrutiny of peer firms. Third, it contributes to the literature on analysts' characteristics by exploring the impact of portfolio complexity on analysts' performance.

Overall, these chapters provide insight into the interaction between the sell-side financial analyst, the central bank, and the external information environment. The findings from these chapters highlight the importance of the central bank's monetary policy in influencing market participants, and the crucial role of the analyst as an information intermediary in transmitting this information. Hence, the findings from this thesis are relevant to policymakers and regulators.

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