Essays on Financial Analysts

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ESSAYS ON FINANCIAL ANALYSTS

ESSAIS SUR LES ANALYSTES FINANCIERS

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ESSAIS SUR LES ANALYSTES FINANCIERS

Résumé général

Les analystes financiers jouent un rôle important dans les marchés financiers. Grâce à la publication de rapports d'analyse, ils facilitent l'incorporation d'informations privées coûteuses dans les prix des titres, favorisant l'efficacité informationnelle des marchés financiers. Ainsi, la compréhension du comportement des analystes a des implications importantes pour les entreprises, les investisseurs et les regulatuers. Malgré des décennies de recherche sur ce sujet, il reste de nombreuses questions ouvertes concernant les renseignements produits par les analystes financiers et la façon dont ces rapports sont influencés par leur environnement de travail.

Dans cette thèse, nous tentons de contribuer à la littérature sur le comportement des analystes et ses effets sur les marchés financiers en abordant plusieurs nouvelles questions de recherche. Les deux premiers articles de cette thèse tentent de mieux comprendre les incitations derrière le biais bien connu des analystes et d'identifier de nouvelles sources de biais. Le troisième article analyse la gouvernance d'entreprise et le rôle des analystes financiers dans la réduction de l'asymétrie d'information.

Le premier article compare le comportement des analystes employés par des banques émettant de la dette avec celui des analystes employés par des banques émettant des actions. Nous nous concentrons sur les différences dans les prix cibles et les recommandations, et nous démontrons que les analystes embauchés par les banques émettrices d'actions sont nettement plus optimistes que les analystes affiliés à des banques souscrivant de la dette. Il est usuellement admis dans la littérature que les analystes sont plus optimistes pour entretenir des relations commerciales avec les entreprises suivies. Notre résultat n'est pas compatible avec cette hypothèse et jette un nouvel éclairage sur les différents conflits d'intérêts qui influencent le comportement des analystes boursiers.

Dans le deuxième article, nous montrons que les analystes dont les employeurs détiennent une participation dans les entreprises suivies émettent des prix cibles et des recommandations beaucoup plus optimistes. Les mises à jour de leurs recommandations génèrent une réaction plus faible du cours de l'action comparées à celles de leurs pairs. La différence d'optimisme entre les analystes propriétaires et non-propriétaires est encore plus grande en période de repli du marché. Ces

résultats mettent en évidence les conflits d'intérêts inhérents aux analystes dont les employeurs détiennent les actions dans les entreprises suivies.

Le troisième article examine de plus près la qualité de la gouvernance d'entreprise et l'effet médiateur du travail des analystes. Nous montrons qu'une rémunération excessive des administrateurs externes est associée à une tendance à ne pas divulguer des informations négatives ce qui créé au final un risque de chute important du cours de l'action. Cette relation est surtout présente pour des directeurs dont la rémunération est indexée sur la valeur de l'action, mais n'est pas présente pour des directeurs dont la rémunération est fixe. Ces résultats permettent d'émettre des doutes sur l'efficacité de la rémunération indexée sur la valeur de l'action qui ne permet pas d'aligner les incitations des administrateurs sur celles des actionnaires. De plus, nous constatons que les entreprises suivies par plus d'analystes ont un risque plus faible de chute des cours de l'action associé à la non-divulgation des mauvaises nouvelles.

ESSAYS ON FINANCIAL ANALYSTS

General abstract

Financial analysts play an important role in capital markets. Through the issuance of analysis reports, they facilitate the incorporation of costly private information into security prices, supporting the informational efficiency of financial markets. Thus, understanding their behavior has important implications for firms, investors, and policy makers. Despite decades of work, there are still many open questions regarding how financial analysts produce and how these reports are influenced by their working environment.

In this dissertation, we attempt at contributing to the literature of analyst behavior and its effects on the capital market by addressing several new research questions. The first two papers of this thesis try to better understand the incentives behind the well-known analyst bias and identify new soucres of bias. The third paper extends into an analysis of corporate governance and the role of financial analysts in alleviating information asymmetry.

The first paper compares analysts affiliated with debt underwriters to analysts affiliated with equity underwriters. We focus on the differences in target prices and recommendations and demonstrate that while equity underwriter analysts are significantly more optimistic in their target prices and recommendations, analysts affiliated with debt underwriters do not exhibit the same bias. While the prominent view in the literature is that equity underwriter analysts are more optimistic to nurture business relationships with the followed firms, the finding that analysts affiliated with debt underwriters behave differently is not consistent with this hypothesis and sheds new light on the different conflicts of interest that influence stock analysts' reporting behavior.

In the second paper, we show that analysts whose employers own a stake in the followed firms issue significantly more optimistic target prices and recommendations. Their recommendation upgrades underperform those of their peers by 0.8% in a two-month window. The difference in optimism between owner and non-owner analysts are even larger in the times of market downturn. These results highlight the conflicts of interest inherent in the analysts whose employers own the followed firms’ stocks.

The third paper looks more closely at the quality of corporate governance and the mediating effect of analyst coverage. We show that excessive compensation of outside directors is associated with bad-news hoarding and stock price crash risk. This relationship is largely attributed to excessive stock-based compensation, but not cash compensation. These findings cast doubts on the effectiveness of stock-based compensation in aligning the incentives of directors with shareholders' interest. In addition, we find that firms followed by more analysts have lower risk of stock price crashes associated with bad-news hoarding.

Contents

1 Introduction

1.1 The role of stock analysts in the capital market

Without information about firms and their projects, financial markets cannot efficiently carry out their function of allocating capital. Some information is freely available to investors, but most information is costly and needs to be generated by well-trained specialists. The profession of financial analysts has evolved to carry out this economic function and provide investors with detailed and specialized public information that would otherwise be very hard to come by. Financial analysts have the necessary combination of technical expertise, industry knowledge and financial acumen that is required to understand the future prospects of companies. They assimilate their hard-earned private information by publishing analyst reports and hence drive stock prices closer to intrinsic values, making the market more informationally efficient and channeling capital flows into promising investments.

Traditionally, analyst reports contain three separate pieces of information : 1) earnings forecasts, 2) price forecasts, and 3) buy, hold, or sell recommendations. We know that these forecasts and recommendations disseminate private information or create new information from public information; because a change in the three types of information has significant impact on the market prices of stocks. Prior research has found that recommendation revisions (Chang and Chan, 2008) and forecast revisions (Park and Stice, 2000, Abarbanell et al., 1995, Gleason and Lee, 2003) trigger investor responses, confirming the informativeness of analyst reports. Specifically, recommendation downgrades and forecast negative revisions are considered as conveying bad information, whereas,

recommendation upgrades and forecast positive revisions are considered as conveying good information.

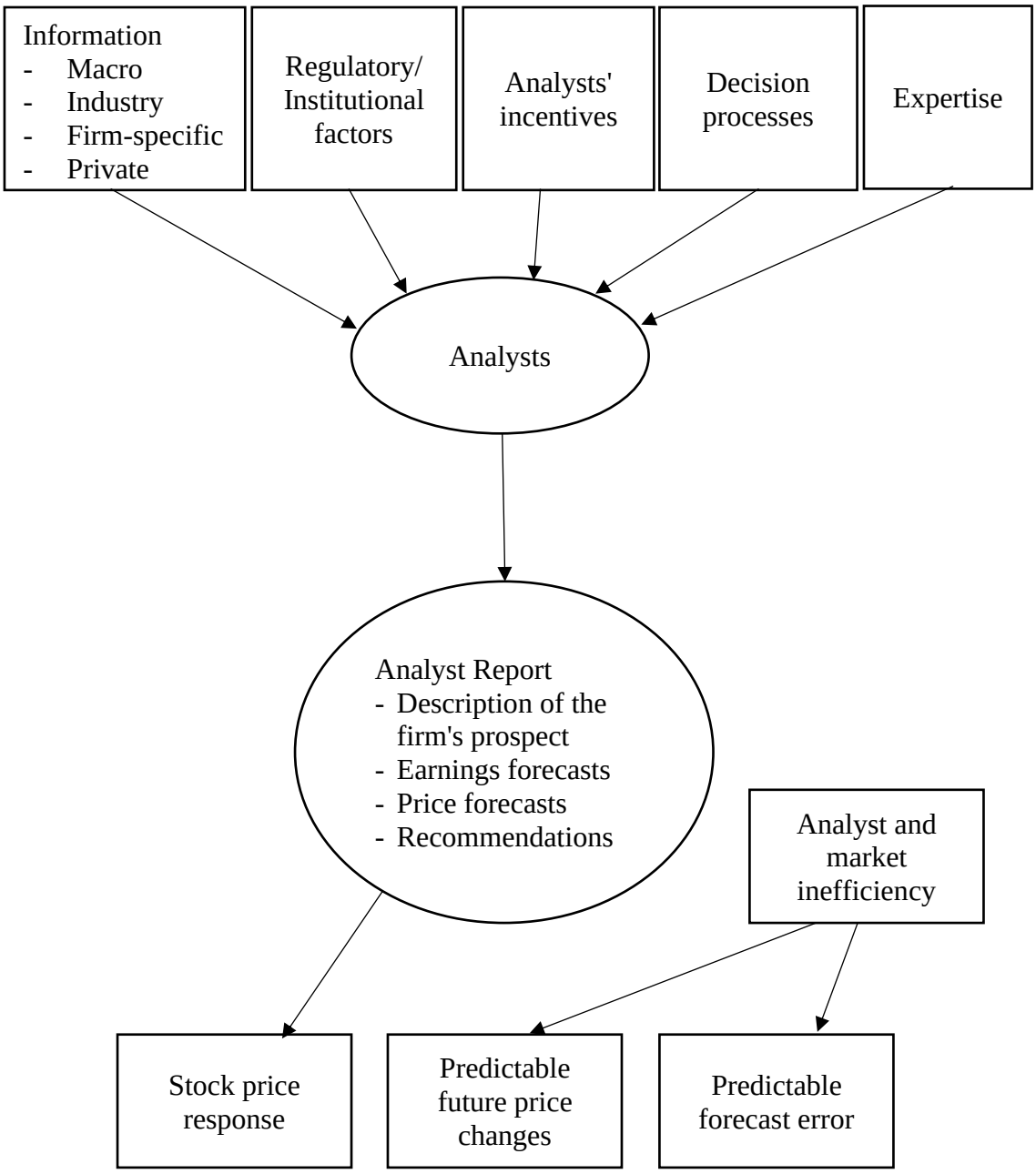

Figure 1: Analysts' reporting environment, adopted and modified from Ramnath et al. (2008).

Figure 1 illustrates the reporting environment surrounding stock analysts. Their input is information from either public or non-public sources. Through the decision processes, assisted and/or constrained by their expertise, incentives, and regulatory or

institutional factors, analysts produce the reports, whose content provides new information to the market and creates stock price movements. Given the important role of stock analysts in the capital market, the properties of their reports have attracted extensive research interest in the last decades. Ramnath et al. (2008) provide a taxonomy of this body of research with seven categories: (1) analyst decision processes, (2) analyst expertise, (3) information content of analyst reports, (4) analyst and market inefficiency, (5) analysts' incentives, (6) regulatory or institutional factors, and (7) research design issues.

This dissertation contributes to the stock analyst literature with several new insights. The first two chapters present studies about how analysts' incentives can distort their forecasts and recommendations. The third chapter explores how analysts assist investors when corporate governance is weak and information asymmetry is high.

This introduction is organized as follows. Section 1.2. provides a literature review on analysts' incentives. Section 1.3 reviews prior studies on the relationship between corporate governance and analyst forecast errors. Section 1.4 introduces the evolution of analyst forecasts during the research period. Section 1.5 briefly discusses the research questions and key findings of the three papers comprising this dissertation.

1.2 Stock analyst conflicts of interest

Stock analysts owe fiduciary duties to the users of their reports and this requires them to be objective in their analysis. Analysts may make errors in their calculations and judgements, but these errors must not be a result of economic incentives. However, as utility-maximizing economic agents, they suffer from various conflicts of interests, which introduce biases in their reports and potentially harm the interest of the reports' users. Understanding these conflicts of interest is vital for policy makers to build a sound and well-

functioning market[1], for investors to make resource-allocating decisions, and for companies to be able to efficiently communicate with policy makers and investors through stock analysts.

Potential economic incentives that may influence stock analyst behavior come from the analyst himself, from his employer and the employer' customers, and management of the followed firm. Key questions are whether these economic incentives systematically affect the analysts' coverage decisions, effort, optimism, etc., and how the market perceives these incentives and reacts to the analyst reports.

Career prospects, reputation and financial benefits are the major personal concerns of financial analysts when issuing stock reports. Hong and Kubik (2003) demonstrate that brokerage houses reward optimistic analysts with more favorable career outcomes, especially those who cover firms with which they have underwriting relationships. A part of analyst optimism also comes from their selective coverage of stocks about which they have favorable expectations and opinions (McNichols and O'Brien, 1997, Das et al., 2006). Raedy et al. (2006a) argue that, as analyst reputation suffers from an asymmetric loss function of future revisions, analysts tend to underreact to earnings information. Chan et al. (2018) find that analysts issue more optimistic target prices for the stocks they own. Breton et al. (2017) show that a close relationship between the firm and the analyst tends to negatively affect forecast accuracy.

[1] Governments around the world has tried to address these conflicts of interest and strengthen investor protection, notably in the US and EU. For example, in 2007, France implemented new rules to unbundle brokerage commission and research fees. Galanti and Vaubourg (2017) find that these rules reduced analyst optimism. Most recently, effective from Jan 3, 2018, the EU's MiFID II regulations require separate pricing between investment research and executive services. In the US, FINRA 2241 rules that the analysts must be "insulated from the review, pressure or oversight by persons engaged in investment banking services activities or other persons, including sales and trading personnel".

In addition, brokerage houses may pressure their analysts to issue biased forecasts to solicit or maintain business relationships. Notably, analysts affiliated with underwriters are more optimistic than non-affiliated analysts (Lin and McNichols, 1998, Dugar and Nathan, 1995). Cowen et al. (2006) show that analysts are more optimistic in their forecasts and recommendations in houses where research is funded by trading commission. Some studies find that analysts are optimistic about stocks in which mutual funds have taken large positions because the funds tend to allocate trading commission fees to the brokerage houses whose opinions about their assets are favorable (Gu et al., 2013, Firth et al., 2013).

Stock analysts are also influenced by the management of the followed firms. There are at least two reasons for this. First, the management of the followed firms is an important source of inputs to guarantee the quality of their reports. Brown et al. (2015) survey financial analysts and find that they value private communication with firm management even higher than their own primary research. Second, the followed firms can be current or prospective customers of the analyst' employers, or potential employers of the analyst himself. One important incentive of the firm management is to meet or beat expectations, as they are rewarded by positive earnings surprises and punished by negative earnings surprises (Matsunaga and Park, 2001, Bartov et al., 2002, Kasznik and McNichols, 2002, Skinner and Sloan, 2002). Archival data and surveys confirm that managers do care about beating analyst forecasts (Brown and Caylor, 2005, Graham et al., 2005). Richardson et al. (2004) find that analysts engage in earnings guidance where they walk-down forecasts to beatable levels in order to assist stock sales by the firms or the managers' personal accounts.

To some extent, the market appears to understand these conflicts of interest embedded in analyst reports. For example, some studies show that the market react less positively to favorable recommendations, and react more negatively to unfavorable

recommendations by analysts affiliated with underwriters of the followed firm (Hirst et al., 1995, Michaely et al., 1999).

1.3 Corporate governance and analyst forecast errors

Prior literature suggests that governance issues substantially influence the accuracy of analyst forecasts. As analysts use financial statements and other firm disclosures as inputs for their reports, governance issues are of important consequence. Kanagaretnam et al. (2007) use the change in market liquidity around quarterly earnings announcements as a proxy for information asymmetry and demonstrate that firms with better quality of corporate governance have lower information asymmetry. Analysts may thus benefit from better corporate governance to produce more accurate forecasts and opinions.

Consistent with this view, Bhat et al. (2006) find that, after controlling for financial transparency, governance transparency and governance-related disclosures significantly improve the information environment and thus improve analyst forecast accuracy. Similarly, Byard et al. (2006) find that better quality of corporate governance improves the quality of financial analysts' information. Xu and Tang (2012) find that analyst forecasts for firms reporting internal control material weaknesses are more optimistically biased and less accurate.

Financial analysts are not simply affected by the informational environment, but also influence the environment. In other word, it is a two-way interaction between the analysts and the environement. Analysts are found to assist information discovery and reduce information asymmetry by either interpreting publicly available information, or disseminating private information through the publication of their research (Ivković and

Jegadeesh, 2004). Analysts have relevant expertise and knowledge, have private interactions with firm management, and their job requires them to follow firms closely. Previous studies found that their reports are informative and valuable, especially when information asymmetry is higher (Ayers and Freeman, 2003, Loh and Stulz, 2018, Charitou et al., 2019).

Analysts are after all agents of residual claims (shareholders and debtholders), and thus are expected to act as an extra layer of external monitors to the firms' managers. Dyck et al. (2010) show that analysts are whistle-blowers in various cases of corporate fraud. Yu (2008) finds that analyst coverage discourages firm management from manipulating earnings.

Prior studies on corporate governance and analyst forecasts, however, are much fewer than other topics of analyst literature. This provides us an opportunity to contribute with new research questions and insights.

1.4 An overview of stock analysts during the past two decades

Figure 2 presents the number of brokerage houses that report to I/B/E/S. Overall, the number of brokerage houses reporting to I/B/E/S increased over time, and peaked at 507 in 2015. A small number of large houses, however, dominate the data. Specifically, the 20 largest houses account for two fifths of earnings forecasts.

Figure 2 also reports the average number of analysts per house. This number also varied substantially during this period. It increased strongly in the late 1990s and early 2000s during the dot-com bubble, but since 2002, has steeply declined to the lowest level of 55 analysts per house in 2009, right after the global financial crisis. Then, the average number of analysts per house has steadily increased to around 70 in recent years.

Figure 3 shows a steady increase in the average number of firms and industries covered by an analyst since 2002, suggesting improved productivity. On average in 2015, an analyst issues earnings forecasts for 17 firms in 3.5 industries. The sharp decline at the beginning of the 2000s in analyst firm and industry coverage corresponds to the contraction of the profession in the aftermath of the dot-com bubble as observed in Figure 2.

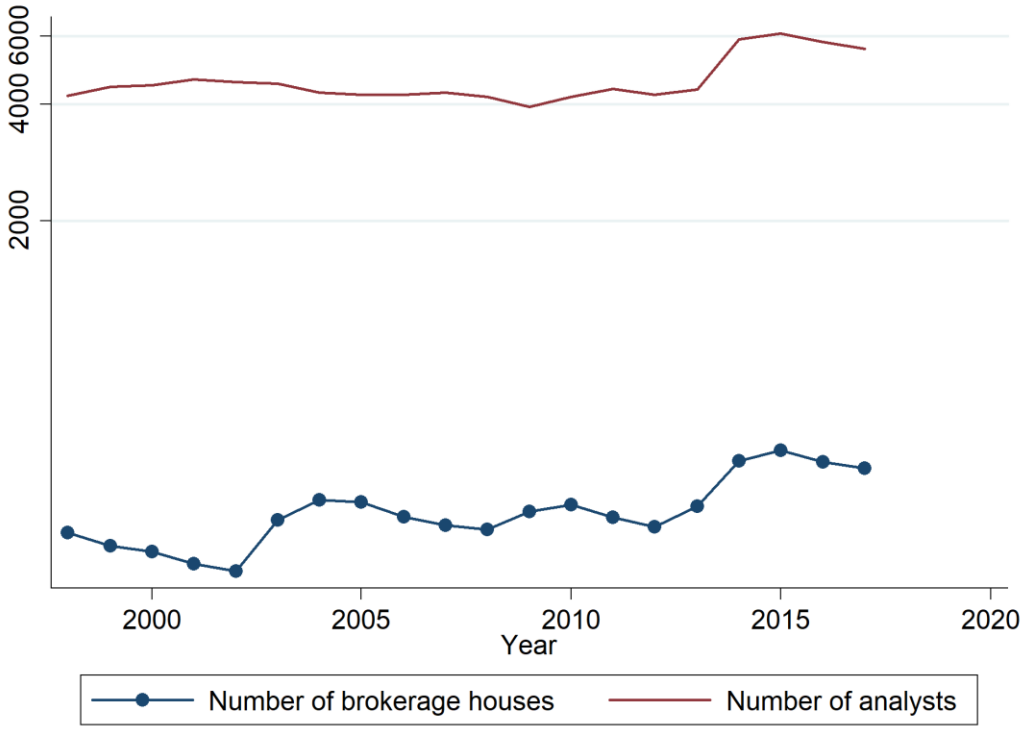

Figure 2: Number of brokerage houses and number of analysts

Figure 4 shows the average number of annual earnings forecast revisions, target price revisions, and recommendation revisions of an analyst for a stock. On average, the frequency of price forecasts and earnings forecasts revisions increases over the studied period. The number of earnings forecast and target price revisions appears to level out at the end of the 2000s, reaching four earnings forecast revisions and three target price revisions for a stock each year. Increased numbers of earnings forecasts and target price revisions indicate increased analyst efforts during this period. The number of recommendations,

however, has decreased overtime, suggesting that recommendations have become more stable than before.

Not surprisingly, the recommendations, and also to a lesser extent earnings and price forecasts, are most frequently revised in the years of financial crisis, such as 2002 and 2008, when uncertainty is high.

Figure 5 presents the evolution of average accuracy of the last annual earnings forecasts (see Chapter 2 for the definition of earnings forecast accuracy). It appears that the accuracy of earnings forecast in general has improved overtime. However, earnings forecasts at times of market turmoil are much less accurate.

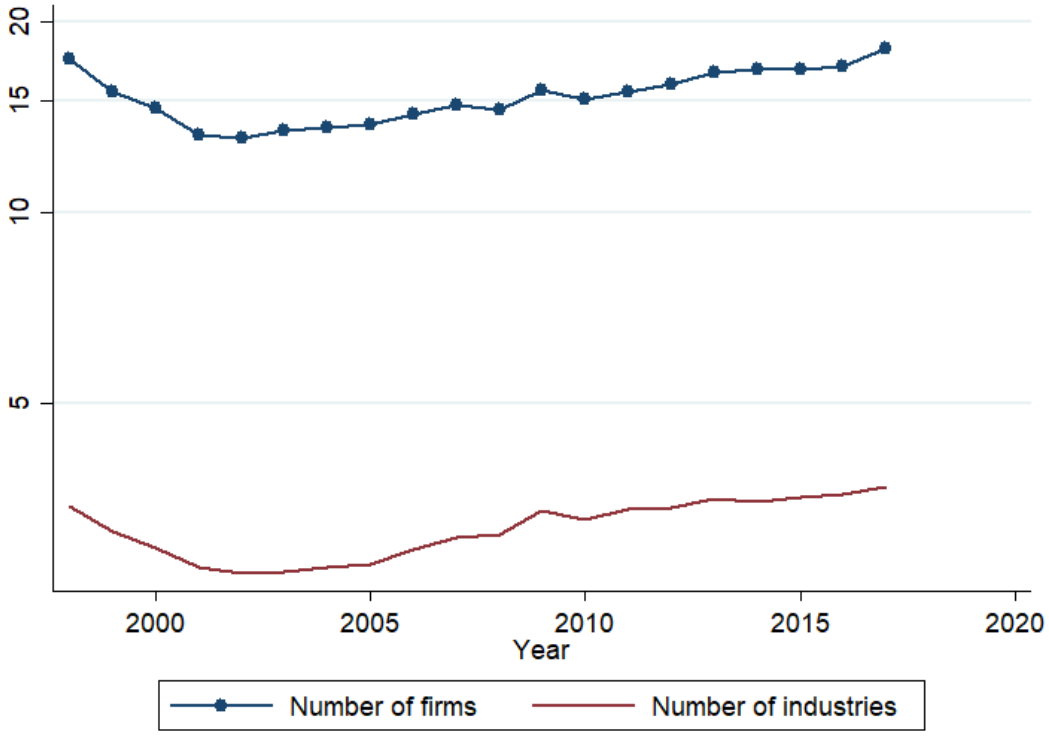

Figure 3: Average number of firms and industries followed by an analyst

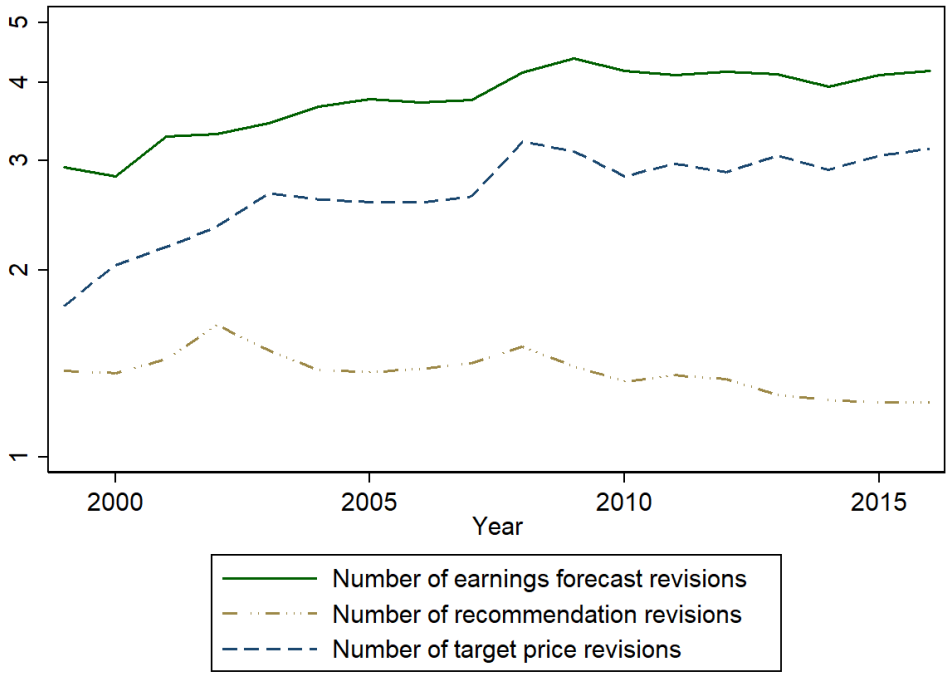

Figure 4: Average number of earnings forecast revisions, target price revisions, and recommendation revisions

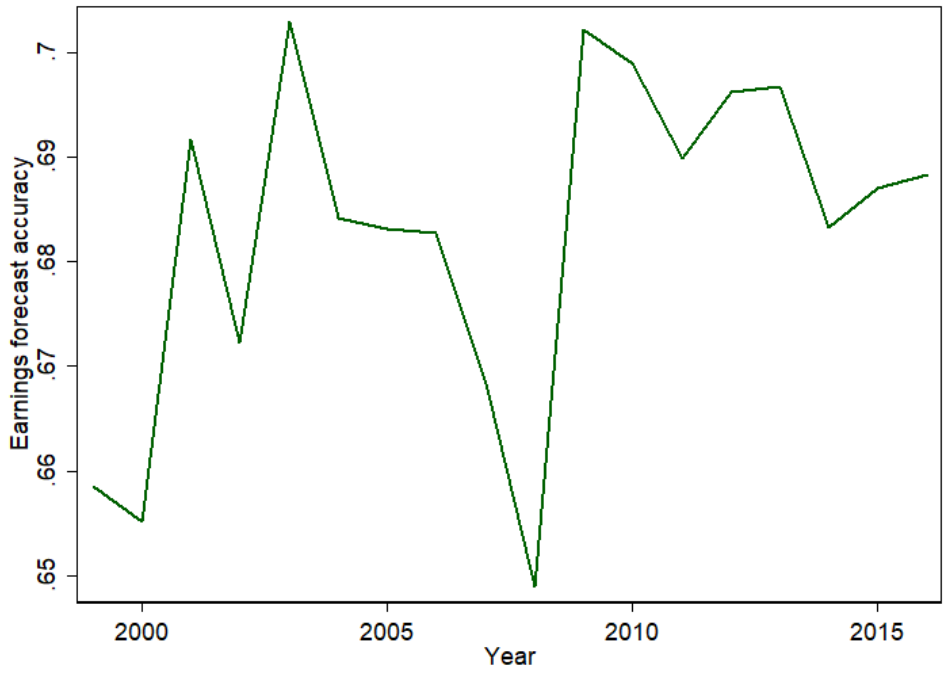

Figure 5: Earnings forecast accuracy

Figure 6 shows the proportion of buy recommendations in the total number of recommendations issued each year. While buy recommendations comprised about 70% of all recommendations in 2000, this proportion declined strongly as the teach bubble busted and stabilized at around 40% after the Global Analyst Research Settlement was reached on April 28, 2003 (SEC, 2003). Since then, the proportion of buy recommendations have been trending up but are still far less frequent than in 2000. Recommendations also exhibit cyclical movements, as they tend to be less favorable in market downturns and more favorable in market expansions.

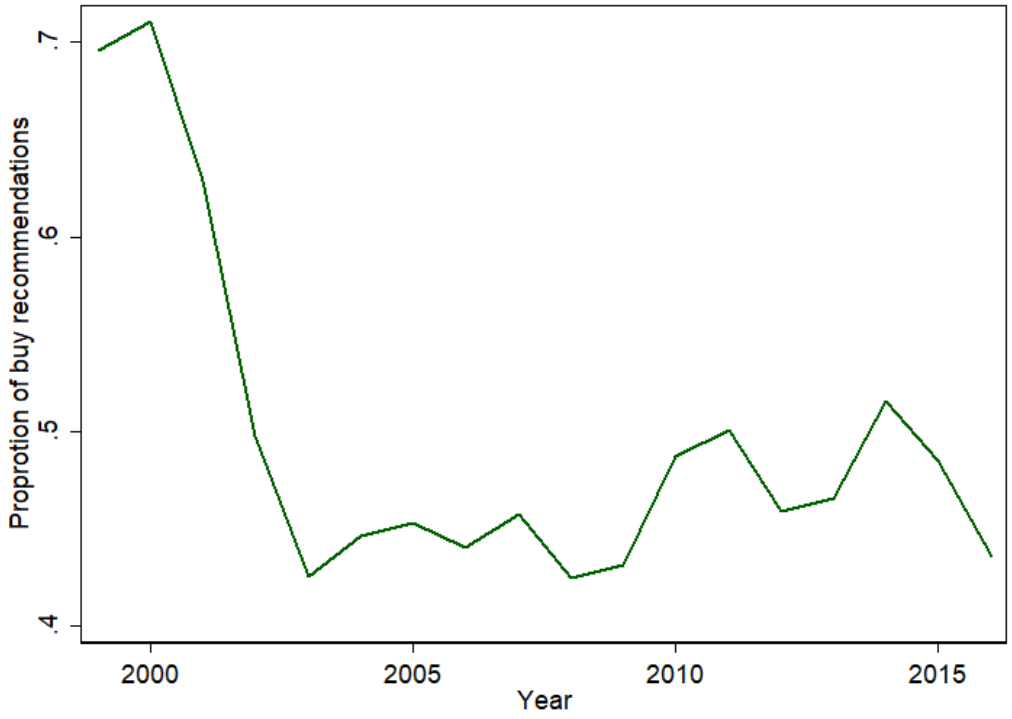

Figure 6: Proportion of buy recommendation in total recommendations

Figure 7 plots the 12-month target price errors by year of target price announcement. This measure of target price errors is calculated as the difference between the target price and the realized price after 12 months, divided by the realized price. Positive target price errors indicate optimism and negative errors indicate pessimism. The graph

reveals several interesting facts. First, over time, target price errors deviate less from zero and from the median, as indicated by the decreasing distance between the 25th and the 75th percentile. This is encouraging because it suggests that over time financial analysts have improved their accuracy, even if part of the effect might also be explained by increased herding in their forecast behavior. Second, forecast errors are much larger and optimistically biased just before market downturns in 2002 and 2008, and then become excessively pessimistic after the market has bottomed out. Almost 75% of forecasts made in 2003 and 2009 are pessimistic. This cyclical pattern of forecasts suggests that analysts are unable to predict a coming market decline or increase, but are instead lagging the market movements. Third, target price errors disperse more widely in the times of market uncertainty (2002 and 2008), as indicated by the wider distance between the 75th and the 25th percentile.

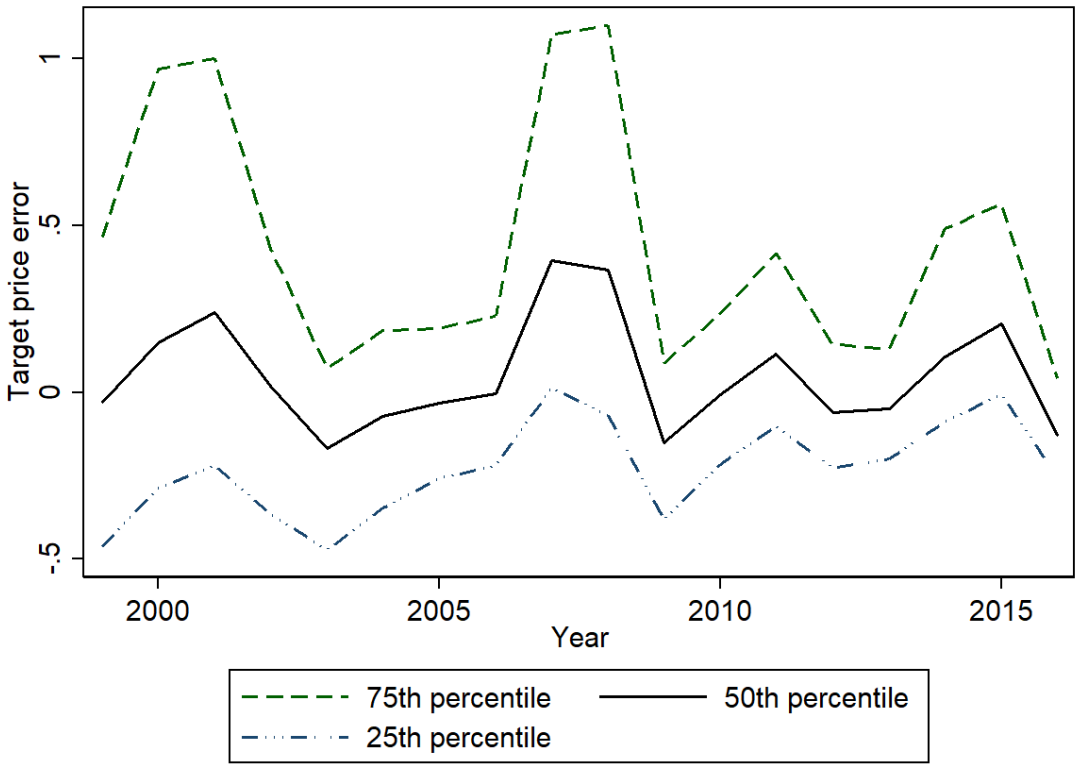

Figure 7: Target price errors

In summary, these figures show that analyst behavior has changed significantly in accordance with the change in their professional environment during the past 20 years. This provides an interesting context to study their behavior in more depths and generate new insights for the academic literature as well as practitioners and policy makers.

1.5 The chapters of this dissertation

Developing on the abovementioned studies, this dissertation presents three papers for a better understanding of financial analyst behavior.

Chapter Two presents the first paper, which revisits the underwriter analysts' conflicts of interest by looking at the behavior of stock analysts affiliated with debt underwriters. The prominent view in the literature is that analysts affiliated with equity underwriters are optimistic to curry business relationship with the followed firms. We show that stock analysts affiliated with debt underwriters are not as optimistic as their counterparts at equity underwriters, suggesting that business relationship is not the incentive behind optimism of equity underwriter analysts. Instead, we argue that they are optimistic due to the need to support the aftermarket performance of the stocks which their employers have underwritten.

The second paper in Chapter Three investigates the relationship between brokerage houses' equity investments and their stock analysts' forecasts and recommendations. We find that analysts whose employers own a stake in the followed firms are significantly more optimistic than their counterparts at non-owner houses.

Finally, in Chapter Four, we investigate the relationship between director compensation, stock price crash risk and analyst coverage. We find that director excessive compensation is associated with significant higher stock price crash risk caused by bad-news hoarding. Analyst coverage can help to alleviate this risk.

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2 Why are analysts optimistic?

Abstract: The paper compares recommendations, target prices, and earnings forecasts of analysts affiliated with debt underwriters to those of analysts affiliated with equity underwriters. We show that analysts affiliated with equity underwriters are optimistic in their target prices and recommendations, whereas analysts affiliated with debt underwriters do not exhibit this bias. This finding contradicts the prominent view in the literature that in order to nurture business relationships with the followed firms, analysts must be optimistic and sheds new light on the different conflicts of interest that influence stock analysts' reporting behavior.

Keywords: affiliated analysts, earnings forecast, target price, recommendation

JEL codes : G14, G24, M41

2.1 Introduction

Financial analysts play an essential role in reducing information asymmetries and increasing market efficiency (Kelly and Ljungqvist, 2012, Derrien and Kecskés, 2013, Ellul and Panayides, 2018). However, the quality of their forecasts and recommendations is affected by a number of conflicts of interests, arising notably from the banking relationship between the analysts' employer and the followed firms (Lin and McNichols, 1998, Degeorge et al., 2007, Dechow et al., 2000, Kolasinski and Kothari, 2008). Existing studies have focused on equity underwriting relationships, and either disregarded debt underwriting relationships, or treated affiliation to debt underwriters and equity underwriters homogeneously. In this paper, we aim at a better understanding of stock analysts' conflicts of interests by comparing the behavior of stock analysts affiliated with debt underwriters to the behavior of analysts affiliated with equity underwriters.

The legal framework has recently evolved to address potential conflicts of interests arising from investment banking activities. Most notably in the US, the Sarbanes-Oxley Act of 2002 and the ensuing Global Analyst Research Settlement of 2003 as well as a series of related SEC and FINRA guidelines recognize that investment banking departments may engage in inappropriate practices that damage the objectivity of research analysts. Essentially, these rules mandate a separation between analysis activities and investment banking activities. FINRA rules also "prohibit explicit or implicit promises of favorable research", and prohibit the analysts from "participation in pitches and other solicitations of investment banking services transactions". These regulatory reforms had a positive effect on mitigating the conflicts of interest, but to a limited extent (Guan et al., 2012, Kadan et al., 2009). In particular and analysts remain very much optimistic. Thus, more research is needed to deepen the understanding of

the issue and help supervisory agencies in improving their oversight and regulations, fostering transparency and fairness in the financial market.

The literature cites at least three conflicts of interest that could explain why that stock analysts are systematically optimistic. First, it has been argued that optimistic stock reports help the analyst's employer to maintain or solicit cordial investment banking business relationships with the followed firms (Cowen et al., 2006, Agrawal and Chen, 2008). This is the dominant view in the literature. Second, analysts can be optimistic to secure their reputation and career prospects in the investment community (Hong and Kubik, 2003, Groysberg et al., 2011, Jackson, 2005). Third, affiliated analysts are alleged to use optimistic forecasts and recommendations to support the aftermarket performance of the financial assets that their employers have underwritten (Schultz and Zaman, 1994, Ellis et al., 2000, James and Karceski, 2006).

To test these conflicts, the literature has focused on analysts affiliated with equity underwriters, who are afflicted by all these three conflicts of interest. As these conflicts result in the same predictions of analysts' optimistic behavior, prior studies cannot distinguish between the different possible mechanisms.

This is where analysts affiliated with debt underwriters provide an interesting subject of research. Unlike their counterparts at equity underwriters, analysts affiliated with debt underwriters are not equally affected by all the three conflicts of interest. They differ in the importance of aftermarket support of the underwritten securities. The reason is simple: debt underwriters are concerned with the aftermarket of debt and not stock. Stock analysts have little influence on the value of debt, given that debt and equity values are only weakly correlated. Stock analysts working at debt underwriters will therefore be relatively impartial about stock price evolution after the offering.

If affiliated analysts are optimistic to curry favor with the followed firms as the prominent view in the literature posit, analysts affiliated with debt underwriters should be as over-optimistic as analysts affiliated with equity underwriters, since they have the same motivation to cultivate banking relationship. However, if affiliated analysts are optimistic in order to support aftermarket stock performance, equity underwriter analysts are much more likely to be optimistic, whereas, debt underwriter analysts have little reason to be so. Thus, by analyzing whether analysts affiliated with debt underwriters are as optimistic as analysts affiliated with equity underwriter, we can confirm which conflict of interest is the key driver behind their optimism.

Our empirical tests show that analysts affiliated with debt underwriters are significantly less optimistic in recommendations and target prices than analysts affiliated with equity underwriters. These findings are robust in our regression analysis, as well as in a propensity score matching procedure. These results do not support the prominent view in prior literature that underwriter-affiliated analysts are optimistic to generate banking relationships but are in line with the conjecture that they are optimistic to support the aftermarket performance of the underwritten securities.

These results have policy implications. While regulations trying to isolate analyst research from the influences of investment banking activities are proliferating, regulations on preventing aftermarket price support appear weak. For example, under FINRA rules, financial analysts and their employers are prohibited from publishing reports or making public appearance relating to the issuer ten days after the initial public offering or three days after the secondary offering where the employer has acted as an underwriter, manager or dealer. Nevertheless, the portfolio turnover ratio of non-index mutual funds in the U.S. is roughly 50%, suggesting that the investors participating in the offering may hold the offered securities for an average of two years (Rowley and Dickson, 2012). The underwriter itself may also retain part

of the offered securities on its own portfolio. Unsurprisingly, academic studies show that underwriter analyst optimism may last for several years. Restrictions of three to ten days thus appear in no way sufficient to prevent underwriters from attempting aftermarket support. Our results therefore suggest that financial analyst regulations should be not only focus on the investment banking relationship but also aftermarket price support.

The rest of the paper is structured as follows: Section 2.2 reviews related literature and develops hypotheses; Section 2.3 introduces the data, methodology and variable construction; Section 2.4 presents selected results; Section 2.5 concludes.

2.2 Literature review and hypothesis development

Prior literature has debated analyst optimism in the different components of stock reports, notably recommendations, target prices, and and earnings forecasts. For example, Lin and McNichols (1998) and Michaely et al. (1999) find that equity underwriter analysts issue more favorable and biased recommendations. Target price optimism is also widespread among stock analysts (Brav and Lehavy, 2003, Asquith et al., 2005, Bradshaw et al., 2013), and is used to justified favorable stock recommendations (Bradshaw, 2002). Analysts at investment banks are also found to trade off earnings forecast accuracy for optimism because of concerns about business relationships or career prospects (Francis and Philbrick, 1993, Hong and Kubik, 2003).

Over-optimism is generated by the analysts' under-reaction to negative information and over-reaction to positive information (Easterwood and Nutt, 1999), and fixation on accounting earnings without accounting for the low persistence of accruals (Bradshaw et al., 2001, Drake and Myers, 2011). This seems to be more a consequence of strategic behavior rather than negligence (Raedy et al., 2006).

These studies generally allege that firm management is fond of optimistic forecasts, and because underwriting relationships are costly to build and maintain, investment banks pressure their analysts to favor overly optimistic forecasts to the detriment of forecast accuracy. Understandably, managers dislike pessimistic opinions about their firms. In his book *Exile on Wall Street: One Analyst's Fight to Save the Big Banks from Themselves*, Mayo (2012) tells the story of how his conservative views of the firms invite hostile reactions from their managers. Moreover, buy recommendations attract more commission revenue from retail investors (Cowen et al., 2006) and institutional investors (Firth et al., 2013, Gu et al., 2013).

Apart from soliciting banking business and brokerage commissions, stock analysts may be optimistic to support aftermarket performance of the stocks their employers have underwritten (James and Karceski, 2006). Aftermarket stock performance concerns arise not only because underwriters have to buy the unsold amount of an offering, but also because the post-offering performance is crucial for their reputation to customers and investors (Bradshaw, 2011). Because favorable coverage can create positive stock price reactions (Asquith et al., 2005, Francis and Soffer, 1997, Jegadeesh and Woojin, 2010), underwriters may pressure their analysts to use favorable analysis reports to support stock performance.

Note that the relationship incentive and the aftermarket performance incentive concern two different groups of the brokerage house' customers. The former are the issuers of the securities the brokerage house has underwritten, whereas the later are buyers of those securities. These two groups of customers may have their interest not necessarily consistent with each.

As previously discussed, analysts affiliated with debt underwriters are as conflicted by the business relationship incentive as analysts affiliated with equity underwriters. However, they are not concerned about the stock performance after the debt has been issued. Therefore, if the business relationship incentive is the dominant determinant of analyst optimism, analysts

affiliated with debt underwriters should be as optimistic as analysts affiliated with equity underwriters. On the contrary, if the aftermarket incentive is the determinant of analyst optimism, analysts affiliated with debt underwriters are not going to be as optimistic. We propose the following hypothesis.

H1: Analysts affiliated with equity underwriters are more likely to be optimistic, while analysts affiliated with debt underwriters are not.

In order to see which incentive is dominant, we run the following regression to test our hypotheses.

$$Optimism/Accuracy = \beta_{0i} + \sum \beta_{mi} Affiliations_{mi} + \sum \beta_{ni} Control_{ni} + \varepsilon_i \quad (1)$$

Where affiliations are dummies indicating the analyst's employment at either a debt underwriter or an equity underwriter of the subject firm. Control variables include firm characteristics, broker characteristics, and analyst characteristics. In all regressions, we control for cross-sectional and temporal biases by normalizing all variables and adding year fixed effects, firm fixed effects, and analyst fixed effects.

2.3 Data and variable construction

2.3.1 Data

We obtain recommendations, target prices and earnings forecasts from U.S. firms and analysts from the I/B/E/S database for the period from 1999 to 2016. We eliminate duplicate observations of the same analyst for the same firm on the same day. For earnings forecasts, we remove forecasts made less than 30 days before the announcement of the actual earnings, forecasts made before the beginning of the financial year, and observations of actual earnings announced later than 100 days after the end of the fiscal year. Following previous literature, we keep only the latest earnings forecasts of a year. We further trim the data by eliminating

extreme observations in the 1st and the 100th percentiles of signed earnings forecast errors. For target prices, we keep only target prices with a target horizon of 12 months. Stock returns are from CRSP, and financial statement data are from Compustat.

We obtain underwriting relationship data from SDC Thomson One Banker. The original equity issue file has 36,944 offerings from 1999 to 2016, among which 589 are initial public offerings. We use both seasoned equity offerings and initial public offerings in our analysis, as is the case in prior studies such as Kadan et al. (2009). As prior studies argue that lead underwriters and co-managers have similar interest in the issuer firms (Bradley et al., 2008), affiliated analysts are defined as those working for either a lead underwriter or a co-manager. This definition is consistent with prior studies (Kadan et al., 2009, Bradley et al., 2008).

In order to test our hypotheses, we need to match this data with I/B/E/S. The common identifier between these two data is the CUSIP number of the issuers in SDC and the followed firms in I/B/E/S. Unfortunately, there is no common identifier to match the underwriters in SDC and the brokerage houses in I/B/E/S.

We circumvent this obstacle using analyst names in the I/B/E/S target price file and recommendation file. In these files, the broker codes are abbreviations of the brokers' names. For example, the three brokers that provided the highest number of target prices are coded "MERRILL" (68,022 observations), "GOLDMAN" (67,526 observations), and "SMITH" (67,077 observations). Codes such as "MERRILL" and "GOLDMAN" can be easily guessed to be Merrill Lynch and Goldman Sachs, but the broker code "SMITH" is less straightforward. We therefore apply the following procedure to uncode all brokerage codes, including the straightforward ones.

We first tabulate analyst names associated with a broker in the latest year for which data are available. We find 99 analysts associated with the broker "SMITH" in 2016,

accounting for 4,227 target prices. We choose analysts whose names are less common and whose numbers of forecasts are large and search their profiles on the internet, such as tipranks.com, LinkedIn, Bloomberg, and company websites. In the case of broker "SMITH" we look at the following names.

"M Bilerman": Search results show an equity analyst Michael Bilerman working for Citigroup in 2016. "S Gruber": An equity analyst Scott Gruber working for Citigroup in 2016. "P Juvekar": An equity analyst PJ Juvekar working for Citigroup in 2016. "K McShane, CFA": An equity analyst Kate McShane, a CFA charter-holder, working for Citigroup in 2016. "G Badishkanian": An equity analyst Gregory Badishkanian working for Citigroup in 2016, etc.

Based on these searches, we assume that "SMITH" represents Citigroup[2]. We repeat this procedure for 149 brokers, accounting for almost 95% of all observations in the target price file and recommendation file. In fact, there are more than nine hundred brokers in the data. However, the 149 brokers we have decoded provided the large majority of observations. The remaining codes refer to less well-known brokerage houses and institutions that have ceased to exist.

Having the name of the brokerage houses in I/B/E/S data, we match the underwriting data into I/B/E/S data using the issuer/subject firm CUSIP number, underwriter/broker name, and year.

There exists an additional problem with the earnings forecast file. The brokerage houses' identifiers in the earnings forecast file are different from those in target price file and recommendation file, and there is no variable containing analyst names in the earnings forecast file. We use the following approximate match procedure to decode the underwriting

[2] We do not know why "SMITH" represents Citigroup. One explanation can be of historical reason. Citigroup previously owned a brokerage house called "Smith Barney". In 2009, it is sold to Morgan Stanley and subsequently renamed "Morgan Stanley Wealth Management".

relationship for earnings forecast file. We assume that analysts are not going to change employers within a given month. We match the decoded broker name from the target price file and recommendation file into the earnings forecast file using analyst code, month and year. This leads to one problem. Assume that brokerage house X in the target price file has another code X* in earnings forecast file, and brokerage house Y in the target price file has another code Y* in the earnings forecast file. Also assume that analyst A worked at brokerage house X on Jan 1st, 2016 and issues a target price, thus presents in price target file. Assume further that on Jan 20th, 2016 A moves to brokerage house Y* and issues an earnings forecast, thus being present in the earnings forecast file. In this case, instead of matching X with X*, we will be matching X with Y*. In other words, if the analyst changes employer within a month and issues target price, recommendation and earnings forecasts on different days of that month, there are chances that his/her employer name will be wrongly matched between the two files.

To account for this, we assume that it is more frequent for A to remain at a brokerage house in a given month than moving from one brokerage house to another. Thus, given a sufficiently large number of observations, the number of matches between X and X* should be significantly larger than the number of matches between X and Y* (and between X and Z*, etc.). Thus, we assume that the pair with the largest number of matches is indeed the correct match (X and X*). All other pairs (X and Y*, X and Z*, etc.) will have much smaller number of matches and are therefore identified as wrong matches.

Using this procedure, we can decode the brokerage houses in the earnings forecast file for 52% of all observations, which is significantly lower than the 95% coverage in the target price and recommendation files.

Prior studies assume that an underwriting relationship lasts from 2 to 5 years after the offering. We assume that the relationship only stretches over a period of two years after date of the security's issuance, in accordance with prior studies such as Kadan et al. (2009). There

are several reasons for why we think that two years is a reasonable time window to test our hypotheses. First, the portfolio turnover ratio of non-index mutual funds in the U.S. is roughly 50%, which implies an investment holding period of 2 years (Rowley and Dickson, 2012). Second, large investors participating in equity issues are very often restricted from selling their shares during the lock-up periods of one year. Our hypothesis is that analysts affiliated with equity underwriters care about the aftermarket of the shares they have underwritten, and thus they may have strong incentives to push stock price within that time frame to support their own portfolio holding or to please the investors who have taken part in the issue.

2.3.2 Dependent variables

In the original dataset, recommendations are coded with values from 1 to 5 corresponding to strong buy, buy, hold, sell, and strong sell recommendation, respectively. It is easier to read the results if higher values represent more positive evaluations. Thus, we recode recommendations by creating the variable *RECOM*, which still has the integer values but in increasing order with 1 corresponding to strong sell until 5 corresponding to strong buy.

In order to test our hypotheses, we need a set of dependent variables that represent analyst precision and optimism in recommendations, earnings forecasts and price targets. We define the following variables:

Recommendations

Intuitively, an analyst is more optimistic if his recommendation is more favorable. We scale all recommendations by the range of recommendations of all analysts for each firm in each year. By construction, this variable has its value ranging from zero to one. Higher values indicate more favorable recommendations.

$$R\_RECOM = \frac{RECOM - \min(RECOM)}{max(RECOM) - \min\,(RECOM)} \quad (2)$$

Besides, an analyst is optimistic if his recommendation is more favorable than those of his peers. We use a relative measure of recommendation optimism. Following prior studies, recommendation optimism (RECOPT) of an analyst for a firm is measured relative to mean recommendation of all analysts for the firm in the last 180 days prior to the day before the recommendation announcement (Gu et al., 2013, Firth et al., 2013).

$$RECOPT = RECOM - mean(RECOM) \quad (3)$$

We also scale RECOPT across all analysts for a firm in a year.

$$R\_RECOPT = \frac{RECOPT - \min(RECOPT)}{max(RECOPT) - \min\,(RECOPT)} \quad (4)$$

Price targets

Most intuitively, target price accuracy can be measured by the distance between the target price and the actual market price at the end of forecast horizon. As we keep only target prices with a 12-month forecast horizon, we measure target price accuracy and optimism relative to realized stock price 365 days after the target is announced (P_{12}). This measure is consistent with prior studies on target prices (Bilinski et al., 2012, Bradshaw et al., 2013, Chan et al., 2018). If a market price at exactly 365 days ahead is not available, we use up to past ten days of market price as substitutes.

$$TPAFE = |TP - P_{12}| \quad (5)$$

$$TPOPT = TP - P_{12} \quad (6)$$

Following Chan et al. (2018), we scale each target price error and optimism by the range of target prices' errors and optimism of all analysts for the firm in the year, as in equation (5) and (6) respectively. This procedure results in two variables ranging from zero to one, with higher values indicating higher accuracy and optimism.

$$TPACCUR = \frac{max(TPAFE) - TPAFE}{max(TPAFE) - min(TPAFE)} \quad (5)$$

$$R\_TPOPT = \frac{TPOPT - \min(TPAFE)}{max(TPOPT) - \min(TPOPT)} \quad (6)$$

Earnings forecasts

Intuitively, users of an analysis report would probably judge the performance of an earnings forecast primarily by how far the forecast is from the actual accounting earnings. We calculate the forecast error (*AFE*) as the absolute value of the distance between actual earnings and forecasted earnings (Jacob, 1997, Mikhail et al., 1997, Mikhail et al., 2003, Drake and Myers, 2011) and optimism (OPT) as the signed difference:

$$AFE = \left|E_{forecast} - E_{actual}\right| \quad (7)$$

$$OPT = E_{forecast} - E_{actual} \quad (8)$$

Jacob et al. (1999) criticize the use of absolute forecast errors for being contaminated by inter-temporal changes and cross-sectional differences. Following Clement and Tse (2005) and similar to what we did for recommendations and prices, we derive a relative measure of forecast accuracy (*ACCUR*). Across all analysts, we subtract the maximum absolute forecast error and optimism for a firm in a year by absolute forecast error of each analyst for the same firm, and scale it by the range of absolute forecast errors and optimism. By construction, these variables have a range from zero to one with higher values indicating more accuracy or optimism.

$$ACCUR = \frac{max(AFE) - AFE}{max(AFE) - min(AFE)} \quad (9)$$

$$R\_OPT = \frac{OPT - \min(OPT)}{max(OPT) - min(OPT)} \quad (10)$$

2.3.3 Independent variables

Our main independent variables of interest include two dummies: *DU* and *EU*, which respectively receive the value of one if the analyst is affiliated with one of the followed firm's

debt underwriters and equity underwriters, and zero otherwise. Because we are concerned with the difference between analysts affiliated with debt underwriters and equity underwriters, *DU* and *EU* must not take the value of one at the same time. We create another variable, *EDU*, which takes the value of one if the analyst's employer underwriters both debt and equity of the followed firm, and zero otherwise.

We consult the literature to add relevant control variables into our models. Mikhail et al. (1997), followed by many other studies, suggest that analysts' individual characteristics could potentially affect forecast accuracy. *GEXPER* is the analyst's general experience, measured by the number of years the analyst has been in our data to the day of the forecast. *FEXPER* is the analyst's firm-specific experience, measured by the number of years the analyst has covered the followed firm in our data to the day of the forecast. *NIND* is the number of 2-digit SIC code industries an analyst covers in a given year. *NFIRM* is the number of firms an analyst covers in a given year. Lower *GEXPER*, *FEXPER*, and higher *NFIRM*, *NIND* may be associated with higher forecast errors (Mikhail et al., 1997, Mikhail et al., 2003, Clement and Tse, 2005). *BSIZE* is the size of the brokerage house, calculated as the number of analysts working for the brokerage house in a given year as observed in the dataset. Larger brokerage houses may be able to make more accurate forecasts because they can attract more talented employees and have more resources. *FREQ* is the number of forecast revisions the analyst issues for a firm in a year. *FREQ* represents analyst efforts. Higher *FREQ* is expected to improve forecast accuracy. *FCAGE* is the number of days from earnings forecast announcement date to announcement of actual earnings. More distant forecasts bear more uncertainty and less updated information, thus are less accurate.

Moreover, Mikhail et al. (2003) show that earnings forecast errors are persistent through time. We add lagged earnings forecast accuracy and optimism as a control variable in

the regressions of earnings forecast accuracy and optimism. We also add earnings forecast accuracy as a control variable in the regressions of target prices and recommendations.

Following prior studies (Clement and Tse, 2005, Chan et al., 2018), analyst characteristics are scaled using the same procedure used for the dependent variables. For each firm each year, an analyst characteristics X is scaled relative to all analysts who issue a forecast for that firm in that year using equation (11).

$$R_X = \frac{X - \min(X)}{\max(X) - \min(X)} \quad (11)$$

We also account for firm-specific factors that may affect analyst forecasts, including book-to-market ratio (*BM*), profitability (*ROA*), leverage (*LEV*) and market capitalization (*MV*). *FOLLOW* is information intensity or analyst competition surrounding a given firm, measured by the number of analysts covering that firm in a given year. Following prior studies, for an analyst in a given year, firm characteristics are scaled across all firms for which the analyst issues a forecast in that year using equation (11) above. Note that analyst characteristics are scaled across all analysts covering the same firm, whereas firm characteristics are scaled across all firms the analyst covers.

In order to control for other potential biases, we also add year fixed effects, industry fixed effects (using two-digit SIC codes), and broker fixed effects to all our regressions.

2.4 Results

2.4.1 Summary statistics

Table 1 shows matched affiliations for each of the I/B/E/S files. Debt underwriter affiliations account for 1.9% observations in the earnings forecast file, 7.9% in the target price file, and 4.6% in the recommendation file. The number of matched affiliations in the earnings

forecast file is lower than in the other files due to the more demanding matching procedure described above.

Table 2 presents summary statistics of our main variables using the earnings forecast file. There are slight differences compared to previous studies, probably due to the difference in our sample selection. For example, Clement and Tse (2003)'s sample has a mean *ACCUR* of 0.58, while ours is 0.68, implying that our sampled earnings forecasts are on average more concentrated around zero forecast errors. This may be due to improved forecast accuracy, or due to our sample selection procedure where we trim 1% of the most inaccurate forecasts at each tail of the distribution of the distance between forecasted and actual earnings.

Table 1: The number of affiliated forecasts and recommendations in each I/B/E/S file

	Earnings forecast		Target price		Recommendation	
	Obs.	Mean	Obs.	Mean	Obs.	Mean
DU	565,558	0.019	716,004	0.079	455,627	0.046
EU	565,558	0.041	716,004	0.071	455,627	0.065
EDU	565,558	0.005	716,004	0.023	455,627	0.016

Prior research does not distinguish between analysts affiliated with equity underwriters and debt underwriters, but Table 2 indicates that they behave quite differently. The first row (*ACCUR*) shows that analysts affiliated with debt underwriters are more accurate as they make smaller earnings forecast errors than analysts affiliated with equity underwriters. This observation is corroborated by Panel B, which shows that analysts affiliated with debt underwriters are more accurate than analysts affiliated with equity underwriters in their target prices.

R_OPT indicates that analysts affiliated with debt underwriters are less optimistic than analysts affiliated with equity underwriters. They also issue less optimistic target prices, as showed in Panel B. The difference in recommendations is not clear.

That both types of affiliated analysts enjoy favorable access to private information, but one is more accurate and the other is optimistic is surprising. Although analysts affiliated with equity underwriters also possess as much advantage as analysts affiliated with debt underwriters, they are unable to translate it into superior accuracy. These statistics supports our hypothesis that their interests are conflicted in different ways.

Regarding analyst characteristics, *BSIZE* reveals that debt underwriters are larger brokerage houses (on average they have 126 analysts per year compared to 66.9 of equity underwriters). Moreover, their analysts are more experienced, as evidenced by higher *GEXPE*. They also have on average longer coverage of a given firm, as indicated by higher *FEXPE*. Mean general experience and mean firm-specific experience are slightly higher than other studies, obviously because our sample spreads through a longer period. *FREQ* shows that debt underwriter analysts revise their earnings forecasts most frequently, suggesting that they pay slightly more efforts than other analysts. These differences may partly explain why analysts at debt underwriters are more accurate. Mean *FCAGE* indicates that on average, an analyst makes the last forecast about four months before announcement date of actual earnings.

Regarding the characteristics of the subject firms, debt issuers appear to be more well-established firms, with larger size, higher profitability, and enjoy higher leverage. Consequently, as *FOLLOW* indicates, they are followed by more analysts than other firms. As analyst competition is higher, analyst accuracy may also be improved.

Table 2: Summary statistics of main variables by the earnings forecast file

Variable definition		Full		Debt Underwriters		Equity Underwriters		Underwriters of both Debt and Equity	
		Obs.	Mean	Obs.	Mean	Obs.	Mean	Obs.	Mean
Panel A: Earnings forecast file									
ACCUR	Earnings forecast accuracy.	558,751	0.684	10,498	0.713	22,987	0.665	3,012	0.689
ROPT	Earnings forecast optimism.	558,095	0.505	10,494	0.508	22,942	0.487	3,013	0.498
GEXPE	The analyst's general experience.	565,557	8.775	10,536	11.554	23,292	9.920	3,030	11.33
FEXPE	The analyst's firm-specific experience.	565,557	2.780	10,536	4.041	23,292	2.003	3,030	2.879
BSIZE	Size of the brokerage house (number of analysts).	565,557	68.97	10,536	126.4	23,292	66.92	3,030	115.9
FOLLOW	Number of analysts following the firm.	565,557	17.28	10,536	20.86	23,292	12.03	3,030	16.48
NFIRM	Number of firms covered by the analyst.	565,557	16.49	10,536	17.56	23,292	17.84	3,030	20.23
NIND	Number of industries covered by the analyst.	521,135	3.286	9,417	3.134	21,201	3.113	2,571	3.188
FREQ	Number of forecast revisions.	565,557	3.849	10,536	4.378	23,292	3.771	3,030	4.415
FIRMAGE	Firm age.	549,670	19.57	10,268	30.34	22,441	11.1	2,844	18.99
ROA	The firm's return-on-assets.	470,206	0.057	8,944	0.084	19,179	-0.020	2,518	0.049
MV	The firm's market capitalization.	481,140	7.858	8,091	9.175	19,745	6.811	2,219	8.067
BM	The firm's book-to-market ratio.	480,713	0.467	8,088	0.472	19,726	0.479	2,204	0.552
LEV	The firm's leverage.	519,728	0.551	9,415	0.696	21,158	0.506	2,571	0.676
FCAGE	Days from the forecast announcement the actual earnings announcement.	565,557	128.8	10,536	123.7	23,292	131.2	3,030	126.2
Panel B: Target price file									
TPACCUR	Target price accuracy.	710,023	0.585	56,825	0.603	50,543	0.566	16,139	0.595
RTPOPT	Target price optimism.	710,025	0.494	56,825	0.491	50,543	0.5	16,139	0.489
Panel C: Recommendation file									
RECOM	Recommendation code.	650,246	2.368	24,408	2.5	40,661	2.284	8,530	2.416
RECOPT	Recommendation optimism.	455,627	-0.05	21,128	-0.085	29,475	-0.078	7,154	-0.05

2.4.2 Recommendation optimism

Table 3 presents the relationship between recommendation optimism and analyst affiliation. In the first regression, *R_RECOM* is *RECOM* transformed by equation (2). In the second regression, *R_RECOPT* is recommendation optimism transformed by equation (4). *EU* and *DU* are dummies indicating the analyst's affiliation with equity underwriter and debt underwriter respectively. We also add relevant variables to control for analyst characteristics and firm characteristics. We also include year fixed effects, firm fixed effects and analyst fixed effects. Standard errors are clustered by subject firms.

The coefficient of *EU* is positive and significant in (1), indicating that equity underwriter analysts are much more optimistic in their recommendations than unaffiliated analysts. The coefficient of *EU* in (2) is also positive, albeit statistically insignificant. Whereas, debt underwriter analysts exhibit no such optimism. These results do not support the banking relationship hypothesis, but are in favor of the aftermarket performance hypothesis.

The coefficients of *ACCUR* is positive and highly significant, suggesting that the ability to predict earnings accurately can support the analyst to make more favorable recommendations. Firm-specific experience shows a negative effects on recommendation optimism. Analysts at larger brokerage houses also appear less optimistic. Analysts who cover more firms are also less optimistic.

Firms with larger market capitalization, and firms that are followed by more analysts, and firms that the analysts put more efforts in on average receive more favorable recommendations.

Table 3: Recommendation optimism and analyst underwriting affiliations

This table presents selected results from the test of analysts' underwriting affiliation and recommendation optimism. The dependent variables measure recommendation optimism. EU and DU are dummies indicating the analyst's affiliation with equity underwriter and debt underwriter respectively. Regressions are fitted using pooled-OLS. t-statistics in parentheses. *, **, *** denote significance levels at 10%, 5%, 1% respectively. See Section 3 and Table 2 for variable definitions.

	(1)	(2)
VARIABLES	R_RECOM	R_RECOPT
EU	0.0129***	0.00654
	(2.675)	(1.261)
DU	-0.00129	0.00106
	(-0.187)	(0.162)
EDU	0.00111	0.00702
	(0.0831)	(0.534)
ACCUR	0.0137***	0.0138***
	(4.471)	(4.103)
R_GEXPE	-0.0146	0.00878
	(-1.506)	(0.741)
R_FEXPE	-0.0267***	-0.0151***
	(-8.524)	(-4.563)
R_BSIZE	-0.0456***	-0.0490***
	(-7.077)	(-6.628)
R_NFIRM	-0.0279***	-0.0332***
	(-5.446)	(-6.122)
R_NIND	0.00374	0.0121**
	(0.835)	(2.489)
R_FREQ	0.00718**	0.00813**
	(2.235)	(2.408)
R_FIRMAGE	-0.00908	-0.0112*
	(-1.530)	(-1.878)
R_FOLLOW	0.0140***	0.0135**
	(2.615)	(2.530)
R_BM	-0.0117***	-0.00205
	(-2.811)	(-0.497)
R_ROA	0.00361	-0.00310
	(0.960)	(-0.816)
R_LEV	0.000183	-6.62e-05
	(0.0393)	(-0.0147)
R_MV	0.0327***	0.0218***
	(5.828)	(3.919)
Constant	0.520***	0.509***
	(66.28)	(60.34)
Observations	172,726	136,161
Year FE	Yes	Yes
Firm FE	Yes	Yes

VARIABLES	(1) R_RECOM	(2) R_RECOPT
Analyst FE	Yes	Yes
Clustered SE	Firm	Firm

2.4.3 Target price accuracy and optimism

Table 4 presents the differences in target price accuracy and optimism between debt underwriter analysts and equity underwriter analysts. Consistent with prior studies, the coefficients of *EU* show that target prices issued by analysts affiliated with equity underwriter are significantly more optimistic than those issued by unaffiliated analysts. On the contrary, analysts affiliated with debt underwriters are not optimistic. The coefficients of *EU* and *DU* in the accuracy regression (1) are contradictory: the former is negative, but the latter is positive, but this result is not statistically significant. That debt underwriter analysts are not optimistic in their target prices is consistent with previous results on recommendations, and does not support the hypothesis that affiliated analysts are optimistic to curry the banking relationship with the subject firms, but rather to support stock price in the aftermarket of the offerings.

The control variables in these regressions show intriguing results. *ACCUR* and *R_OPT* are positive and highly significant, consistent with prior studies which argue that earnings forecasts are used to justify target prices and recommendations. More experienced analysts and analysts who cover the firm for longer time are even less accurate, but these results are only weakly significant. Analysts working at larger brokerage houses are less optimistic.

Firm-level characteristics also affect analyst forecasting behavior. Firms with larger capitalization receive more optimistic forecasts, which are also more accurate. Competition also appears to improve price forecasts, as target prices for firms that are followed by more analysts are more accurate. More profitable firms and more leveraged firms receive more optimistic target prices.

Table 4: Target price accuracy and optimism and analyst underwriting affiliations

This table presents selected results from the test of analysts' underwriting affiliation and target price accuracy and optimism. TPACCUR is target price accuracy. R_TPOPT is target price optimism. EU and DU are dummies indicating the analyst's affiliation with equity underwriter and debt underwriter respectively. Regressions are fitted using pooled-OLS. t-statistics in parentheses. *, **, *** denote significance levels at 10%, 5%, 1% respectively. See Section 3 and Table 2 for variable definitions.

	(1)	(2)
VARIABLES	TPACCUR	R_TPOPT
EU	-0.00292	0.0178***
	(-0.730)	(4.384)
DU	0.00874	0.00469
	(1.583)	(0.968)
EUD	-0.00612	0.0146*
	(-0.586)	(1.671)
ACCUR	0.0137***	
	(4.802)	
R_OPT		0.0330***
		(12.40)
R_GEXPE	-0.0224**	0.00558
	(-2.270)	(0.580)
R_FEXPE	-0.00485*	0.00445
	(-1.719)	(1.620)
R_BSIZE	0.00496	-0.0157***
	(0.792)	(-2.595)
R_NFIRM	-0.00557	-0.00426
	(-1.119)	(-0.909)
R_NIND	0.00485	0.00639
	(1.193)	(1.576)
R_FREQ	-0.00221	0.00654**
	(-0.760)	(2.386)
R_FIRMAGE	0.00401	0.00164
	(0.749)	(0.303)
R_FOLLOW	0.0165***	-0.00472
	(3.106)	(-0.949)
R_BM	-0.00655	0.00710*
	(-1.629)	(1.825)
R_ROA	-0.00492	0.00658*
	(-1.333)	(1.788)
R_LEV	-0.0122**	0.0121***
	(-2.464)	(2.686)
R_MV	0.0105**	0.00966*
	(1.966)	(1.876)
Constant	0.579***	0.465***
	(75.16)	(64.56)
Observations	237,664	237,705
Year FE	Yes	Yes

VARIABLES	(1) TPACCUR	(2) R_TPOPT
Firm FE	Yes	Yes
Analyst FE	Yes	Yes
Clustered SE	Firm	Firm

2.4.4 Earnings forecast accuracy

Table 5 shows selected results for our multivariate tests of the relationships between the types of affiliations and earnings forecast accuracy and optimism. We use *ACCUR* to surrogate analyst earnings forecast accuracy and *R_OPT* to surrogate optimism. There is no statistical difference observed between analysts affiliated with equity underwriters and debt underwriters in these regressions.

Consistent with prior studies, the coefficients of *FCAGE* shows that later forecasts are more accurate (Mikhail et al., 1997, Clement, 1999), as information becomes available and uncertainty is reduced. Earlier forecasts are also more optimistic, which is in accordance with the walk-down-to-beatable-forecast hypothesis (Richardson et al., 2004). The coefficient of lagged *ACCUR* and lagged *R_OPT* are positive and highly significant, suggesting that analyst forecast errors are persistence in time, which is consistent with Mikhail et al. (2003).

Total number of firms (*NFIRM*) or industries (*NIND*) followed by an analyst are used to measure task complexity or divided efforts (Clement, 1999). Our results show that the more firms the analyst cover, the more accurate his earnings forecasts are, as indicated by the coefficient of *NFIRM*. However, if he covers more industries, his earnings forecast accuracy declines, perhaps as a consequence of divided efforts. More revisions of the forecast also make it more accurate and less optimistic, as suggested by the coefficients of *FREQ*.

Table 5: Earnings forecast accuracy and analyst underwriting affiliations

This table presents selected results from the test of analysts' underwriting affiliation and earnings forecast accuracy and optimism. ACCUR is target price accuracy. R_OPT is target price optimism. EU and DU are dummies indicating the analyst's affiliation with equity underwriter and debt underwriter respectively. Regressions are fitted using pooled-OLS. t-statistics in parentheses. *, **, *** denote significance levels at 10%, 5%, 1% respectively. See Section 3 and Table 2 for variable definitions.

	(1)	(2)
VARIABLES	ACCUR	R_OPT
EU	0.00228	-0.00349
	(0.587)	(-0.759)
DU	-0.00500	-0.00556
	(-1.134)	(-1.103)
EDU	0.00606	-0.000505
	(0.673)	(-0.0506)
lag(ACCUR)	0.0174***	
	(5.627)	
lag(R_OPT)		0.0259***
		(6.509)
R_GEXPE	-0.00959	-0.00197
	(-1.267)	(-0.213)
R_FEXPE	-0.000791	0.00107
	(-0.301)	(0.355)
R_FCAGE	-0.291***	0.0471***
	(-75.41)	(9.966)
R_BSIZE	-0.00471	-0.00153
	(-1.016)	(-0.270)
R_NFIRM	0.0159***	-0.000484
	(3.699)	(-0.0851)
R_NIND	-0.00808**	0.00802*
	(-2.246)	(1.781)
R_FREQ	0.0701***	-0.0135***
	(22.22)	(-3.454)
R_FIRMAGE	-0.0126***	-0.0114*
	(-2.640)	(-1.836)
R_FOLLOW	0.0671***	-0.0560***
	(13.69)	(-7.859)
R_BM	-0.00617*	-0.0473***
	(-1.781)	(-9.241)
R_ROA	0.00341	0.0340***
	(1.049)	(6.907)
R_LEV	-0.0117***	-0.0186***
	(-2.981)	(-3.168)

VARIABLES	(1) ACCUR	(2) R_OPT
R_MV	0.0109**	0.0323***
	(2.333)	(5.251)
Constant	0.720***	0.513***
	(99.74)	(58.91)
Observations	257,234	256,857
Year FE	Yes	Yes
Firm FE	Yes	Yes
Analyst FE	Yes	Yes
Clustered SE	Firm	Firm

Firm characteristics also appear to affect analyst accuracy. Analysts seem to be more accurate in forecasting firms that are followed by more analysts, firms that have larger market capitalization, use less debt and have higher boo-to-market ratio.

2.4.5 Suspected guided forecasts

Our results above do not support the hypothesis that overly optimistic coverage is intended to curry favor with the followed firms. We are not the first to raise doubt about this hypothesis (Bradshaw, 2011). Analyst optimism creates expectations that firm management cannot meet, thus disappoints investors, harms the managers' long-term reputation and depresses stock prices (Graham et al., 2005). Ciccone (2003) shows that optimistic expectations lead to investor disappointment and underperformance of stock returns. Stock price crash risk is also more pronounced when analysts are more optimistic (Xu et al., 2013). Additionally, Ljungqvist et al. (2006) find no evidence that overoptimistic analysts help the banks attract underwriting mandates.

There is a large literature suggesting that the followed firm's management does not fancy overoptimistic opinions. Degeorge et al. (1999) demonstrate that managers have strong incentives to "meet or beat" analysts' forecasts. Bartov et al. (2002) demonstrate that

consistently reporting positive earnings surprises creates higher stock returns and stock valuations that cannot be explained by the firm's performance. This view is corroborated by numerous studies from the earnings management and forecast management literature (Matsumoto, 2002, Burgstahler and Eames, 2006, Roychowdhury, 2006, Beyer, 2008, Bernhardt and Campello, 2007, Quinn, 2018). According to this strand of studies, management is actively involved in guiding analyst forecasts downwards, so that they can meet expectations or achieve small positive earnings surprises (Burgstahler and Eames, 2006, Bartov et al., 2002, Athanasakou et al., 2009, Athanasakou et al., 2011). Examining how earnings forecasts evolve through time, Richardson et al. (2004) find that analysts start out optimistic and later "walk-down" forecasts to the levels that the firm can beat.

Table 6 examines whether affiliated analysts are more likely to issue beatable forecasts to help firm management realize positive surprises. Suspected beatable forecasts (*SUSPECT*) are defined as those lower than realized earnings by less than 10 cent of a dollars. Because the dependent variable is a dummy, we use random effect probit regressions in column (1). Unreported rho (ρ) is different from zero, suggesting that the proportion of the total variance contributed by the panel-level variance component is important and thus pooled estimator is biased.

Regression (1) indicates that analysts affiliated with equity underwriters are significant less likely to issue beatable forecasts that are slightly pessimistic, even less likely than unaffiliated analysts. This again supports our conjecture that analysts affiliated with equity underwriters are optimistic probably not solely due to business relationship concerns.

Table 6: Suspected forecasts and analyst underwriting affiliations

This table presents selected results from the test of analysts' underwriting affiliation and suspected earnings forecasts. SUSPECT is a dummy indicating suspected earnings forecasts. EU and DU are dummies indicating the analyst's affiliation with equity underwriter and debt underwriter respectively. Regression (1) is fitted using a random effect probit model. Regression (2) is fitted using a pooled-OLS model. z-statistics and t-statistics in parentheses. *, **, *** denote significance levels at 10%, 5%, 1% respectively. See Section 3 and Table 2 for variable definitions.

	(1)	(2)
VARIABLES	SUSPECT	SUSPECT
EU	-0.0804***	0.00630
	(-3.124)	(1.038)
DU	0.00224	-0.00734
	(0.0810)	(-1.034)
EDU	-0.0817	0.000743
	(-1.509)	(0.0545)
lag(ACCUR)	0.0689***	0.0101**
	(4.277)	(2.303)
R_GEXPE	0.0732***	0.00828
	(5.064)	(0.724)
R_FEXPE	-0.133***	0.00602
	(-6.664)	(1.482)
R_FCAGE	-0.564***	-0.161***
	(-29.16)	(-28.72)
R_BSIZE	-0.0312**	-0.0106
	(-2.294)	(-1.476)
R_NFIRM	0.0391*	0.0122
	(1.911)	(1.624)
R_NIND	0.000545	-0.00151
	(0.0273)	(-0.256)
R_FREQ	0.207***	0.0592***
	(11.48)	(11.91)
R_FIRMAGE	0.0315	0.00588
	(0.809)	(0.735)
R_FOLLOW	-0.0510	-0.0624***
	(-1.332)	(-6.073)
R_BM	-0.259***	-0.0486***
	(-9.435)	(-7.138)
R_ROA	0.340***	0.0787***
	(14.03)	(11.85)
R_LEV	-0.222***	-0.0531***
	(-7.074)	(-6.598)
R_MV	0.296***	0.0279***
	(7.989)	(3.347)
Constant	-0.334***	0.453***
	(-8.028)	(38.96)
Observations	258,462	257,311

VARIABLES	(1) SUSPECT	(2) SUSPECT
Year FE		Yes
Firm FE		Yes
Analyst FE		Yes
Clustered SE	Firm	Firm
Number of code	92,313	

This specification of random effect probit model is, however, not consistent with previous regressions in the use of fixed effects. Probit model does not allow fixed effects, whereas high levels of fixed effects in our data (about 4,800 firms, 8,600 analysts, 18 years) make it difficult to apply other equivalent logistic models. As long as we care about the signs of the regression coefficient, OLS has been used in previous studies (Horrace and Oaxaca, 2006). In column (2), we fit the regression using OLS with all the fixed effects used previously. In this specification, the coefficients of affiliation variables are not statistically significant.

2.4.6 Matched samples

In this part, we perform propensity score matching using the nearest neighborhood matching between analysts affiliated with debt underwriters (treated group) and analysts affiliated with equity underwriters (control group). Matching variables are *R_OPT, R_GEXPE, R_FEXPE, R_BSIZE, R_NFIRM, R_NIND, R_FREQ, R_FIRMAGE, R_FOLLOW, R_BM, R_ROA, R_LEV, R_MV*, industries and years. We also apply the value for maximum propensity score distance of controls to be 0.01. The results of the tests are reported in Table 7. ATTs of *R_RECOM*, and *R_REOPT* show that the average effects of treatment on the treated (debt underwriter analysts compared to equity underwriter analysts) are negative and highly significant, suggesting that analysts affiliated with debt underwriters are much less optimistic than analysts affiliated with equity underwriters. Moreover, ATT of *TPACCUR* is positive and

highly significant, suggesting that debt underwriter analysts are more accurate than equity underwriter analysts. These are consistent with our results in the previous sections.

Table 7: Propensity score matching

This table shows the average treatment effect based on propensity score matching using nearest neighborhood matching. The treatment group is analysts affiliated with debt underwriters. The control group is analysts affiliated with equity underwriters. Matching variables are R_OPT, R_GEXPE, R_FEXPE, R_BSIZE, R_NFIRM, R_NIND, R_FREQ, R_FIRMAGE, R_FOLLOW, R_BM, R_ROA, R_LEV, R_MV, industry dummies and year dummies. t-statistic is shown in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels. See Section 3 and Table 2 for variable definitions.

	ATT (average effect of treatment on the treated)
R_RECOM	-0.04396***
	(-4.07)
RRECOPT	-0.0294***
	(-2.83)
RTPOPT	-0.00732
	(-1.15)
TPACCUR	0.023949***
	(3.63)

In Table 8, we regress recommendation optimism with *TREAT* in the subsample of matched pairs of observations resulting from the propensity score matching procedure in Table 7. *TREAT* is a dummy which equal one if the analyst is affiliated with debt underwriter and zero if the analyst is affiliated with equity underwriter. We include all control variables and also firm fixed effects, analyst fixed effects, and year fixed effects. Although the matching procedure generates 1,487 pairs of matches, corresponding to 2,974 observations, the number of observations in these regressions are significantly lower due to exclusion of singleton observations as we use fixed effects estimation. The coefficient of *TREAT* is still statistically significant in column (2), despite the small matched sample and extensive control of fixed effects. This coefficient is negative, suggesting that debt underwriter analysts (treated group) is less optimistic than equity underwriter analysts.

Table 8: Recommendation optimism and analyst underwriting affiliations

This table presents selected results from the test of analysts' underwriting affiliation and recommendation optimism. The dependent variables measure recommendation optimism. EU and DU are dummies indicating the analyst's affiliation with equity underwriter and debt underwriter respectively. Regressions are fitted using pooled-OLS. t-statistics in parentheses. *, **, *** denote significance levels at 10%, 5%, 1% respectively. See Section 3 and Table 2 for variable definitions.

	(1)	(2)
VARIABLES	R_RECOM	RRECOPT
TREAT	-0.0698	-0.0833*
	(-1.234)	(-1.694)
R_OPT	-0.00982	-0.0156
	(-0.249)	(-0.432)
R_GEXPE	-0.273	-0.156
	(-1.390)	(-0.839)
R_FEXPE	0.122**	0.0308
	(2.161)	(0.602)
R_BSIZE	-0.0286	-0.0263
	(-0.241)	(-0.247)
R_NFIRM	-0.176**	-0.0732
	(-2.388)	(-1.080)
R_NIND	0.0980	0.0147
	(1.564)	(0.266)
R_FREQ	-0.00278	-0.0151
	(-0.0569)	(-0.351)
R_FIRMAGE	-0.103	-0.190*
	(-0.828)	(-1.662)
R_FOLLOW	0.0162	0.0679
	(0.209)	(1.001)
R_BM	-0.0470	-0.0277
	(-0.684)	(-0.444)
R_ROA	0.00241	-0.00717
	(0.0415)	(-0.141)
R_LEV	0.0963	0.0792
	(1.342)	(1.306)
R_MV	-0.00505	0.0628
	(-0.0528)	(0.742)
Constant	0.700***	0.649***
	(3.952)	(4.089)
Observations	2,146	2,151
Year FE	Yes	Yes
Firm FE	Yes	Yes
Analyst FE	Yes	Yes
Clustered SE	Firm	Firm

In conclusion, our empirical results illustrate the behavioral difference of analysts affiliated with debt underwriters and equity underwriters. This difference cannot be explained by the well-established banking relationship hypothesis in the literature. Optimism of equity underwriter analysts is likely to comes from the need to support the security price in the aftermarket.

2.5 Conclusion

By analyzing the differences in accuracy and optimism between analysts affiliated with debt underwriters and equity underwriters, we demonstrate that optimism is not primarily driven by the underwriter's relationship building with the covered firms, but by its concern for the aftermarket performance of the underwritten securities.

Our results also indicate that information flows from debt underwriting division to equity research division within an investment bank, helping stock analysts produce superior forecasts. This is in accordance with prior literature. For example, Chen and Martin (2011) demonstrate that commercial banking relationship with the covered firms significantly improves analysts' accuracy, suggesting that information is shared between commercial banking division and equity research division. Hwang et al. (2019) show that after M&As, the acquirer-analysts' earnings forecasts for merged firms are substantially more accurate if they have in-house colleagues covering target firms prior to M&As.

Other papers support the observations by prior studies that information is shared among different departments within a financial institution (Haushalter and Lowry, 2011). Perhaps most related to our study, Hugon et al. (2016) suggest that equity analysts benefit from in-house debt research, particularly from cash-flow forecasts in debt research. This view is corroborated by a number of studies showing that analysts' earnings forecasts and target prices

are more accurate if they are supported with cash flow forecasts (Call et al., 2009, Mohanram, 2014, Radhakrishnan and Wu, 2014, Hashim and Strong, 2018).

However, our paper does not answer how the organizational structure within a brokerage house, i.e. whether they have joint or separate debt research department and equity research department, may affect the analysts' conflicts of interest and their behavior. This can be a potential direction of future research.

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3 Stock analysts' behavior when their employers own shares in the covered firms

Abstract: We show that analysts whose employers own a stake in the followed firms issue significantly more optimistic target price and recommendations. Owner analysts also appear to cooperate more closely with the firm to publish beatable forecasts. Owner analysts' recommendation changes do not appear to be more informative than others, as they do not create larger market reactions. Quite the contrary, their recommendation upgrades lead to 0.8% lower price increases within two months. Finally, we find that owner analysts become even more optimistic than their peers in times of market turmoil. These results highlight the conflicts of interest inherent in analysts whose employers own the covered firms' stocks.

Keywords: stock analysts, earnings forecasts, ownership, insider trading

JEL codes : G14, G24, M41

3.1 Introduction

Stock analysts support the informational efficiency of the market by issuing reports about publicly traded companies that provide estimates of future earnings and stock prices. They also give recommendations based on which investors can buy, hold, or sell stocks. It has been well documented that these reports contain valuable information and that the market reacts strongly to changes in their content (Asquith et al., 2005).

However, stock analyst integrity and thus their reports' can be compromised by a number of conflicts of interest. That financial analysts publish biased forecasts is a serious concern of shareholders, regulators and other stakeholders (Kolasinski and Kothari, 2008, SEC, 2010). In the US, the SEC (2010) identifies four categories of potential conflicts of interest: investment banking relationships, brokerage commission, analyst compensation and ownership interest in the company. The first three of these categories have been extensively researched in prior literature (Lin and McNichols, 1998, Cowen et al., 2006, Hong and Kubik, 2003). As a result, immense efforts have been aiming at curbing them to protect investors. For example, FINRA rule 2241 sets out strict rules that try to insulate research analysts from the influences of investment banking, sales and trading personnel, as well as of compensation designs.

However, very few studies have analyzed the effects of the last category of conflicts of interest, i.e. stock ownership, on analyst behavior. The SEC (2010) mentions three types of ownership that potentially compromise analysts' integrity: ownership by the analyst, by other employees and finally by the analyst's employer. The first of these conflicts has been investigated by Chan et al. (2018), who find that analysts who personally own a stake in the followed firms are more optimistic in their target prices. They even demonstrate that analysts trade against their recommendations, despite an explicit regulatory prohibition in FINRA rule 2241, suggesting that law enforcement in this area is ineffective. No one has examined the

effects of the analyst's employer's equity investment in the subject firm on his reports. We venture to fill this gap in the literature with this paper.

Our data show that around 26% of all recommendations in the I/B/E/S database are made by analysts whose employers own at least $1 million worth of the followed stocks in the quarter when the recommendations are made or up to two quarter before. This suggest that ownership by analysts' employers in the followed firms is a surprisingly widespread phenomenon that is worth attention.

Combining stock investments and stock analyst research in the same brokerage house does not need to have only negative effects on the analyst's performance. Analysts benefit from their employers' resources (Malloy, 2005, Green et al., 2014, Soltes, 2014, Brown et al., 2015). As institutional owners have superior informational advantage (Ke and Petroni, 2004, Piotroski and Roulstone, 2004, Bushee and Goodman, 2007, Yan and Zhang, 2007), owner analysts' forecasts and recommendations can be more informative and accurate. Moreover, analysts and their employers have stronger incentives to carefully observe, monitor and analyze the companies that they have a stake in. This increased effort can improve the quality of their stock reports. Additionally, suspected partiality may subject analysts working at stock owning brokers and their employers to closer scrutiny by supervisory agencies. Brokerage houses and analysts may therefore abide by law and be impartial even if they have conflicts of interest. Consistent with this view, in a study closely related to ours, Kang et al. (2016) find that when a brokerage house has a venture capital investment in an IPO issuer, its analysts are less likely to be over-optimistic about the issuer, and their recommendations are also more informative. One may question the ability of analysts to benefit from such informational resources due to legal strictures or segmentation between different departments in a financial firm. Nevertheless, prior research offers extensive evidence on analysts taking advantage of information from other departments in a financial firm. For example, Chen and Martin (2011) show that analysts whose

employers have lending relationships with the followed firms are more accurate. Hwang et al. (2019) find that post-M&A earnings forecasts are more accurate if the analyst's colleagues cover the target firm pre-M&A. Other studies show that stock analysts benefit from the information of other departments, such as in-house asset managers (Haushalter and Lowry, 2011) and debt analysts (Hugon et al., 2016).

Obviously, there exist also concerns that potential conflicts of interest resulting from equity investments in the followed firms may damage the objectivity of owner analysts' reports. Such conflicts of interest may arise not only from trading in the followed stocks, but also from holding them. To account for equity investments, firms in the U.S. use two accounting standards: the U.S. GAAP and the IFRS, both of which to a large extent use fair value accounting of equity investments. Hence if the market value of stocks declines, this negatively affects the balance sheet of the owner, and also impacts the income statement or comprehensive income statement, and thus the owner's financial position as it appears on the financial statements. An impairment of significant equity investments may put pressure the owner's stock price and the reputation or compensation of the its management. Therefore, it is not surprising that institutional owners have been found to favor optimistic opinions about stocks they own, and to some extent use their bargaining power to coerce others to agree with them. For example, Gu et al. (2013) show that mutual funds pressure brokerage analysts through allocation of trading commission fees to issue optimistic recommendations for the stocks which the funds have taken large positions. Firth et al. (2013) find the same conclusion and add that analysts who are supposedly pressured by mutual funds are less likely to incorporate bad news in their recommendations. Although these two studies are not exactly about the type of ownership we study in this paper, they suggest that brokerage house owners may have the same incentives to be optimistic, and this can affect their analysts' behavior.

Our study tries to understand the importance of the positive and negative effects deriving from stock ownership that we described above and analyze whether overall, the employer's ownership in the followed firms improves or damages the analysts' performance. Consistent with the later view, we find that owner analysts are more likely to issue optimistic target prices and recommendations. The difference in optimism between owner analysts and non-owner analysts is even larger in the times of market crisis. Moreover, owner analysts are more likely to publish forecasts slightly below realized earnings. Slightly pessimistic earnings forecasts are an indication of guided forecasts used by stock analysts to support the followed firms' management and stock price (Burgstahler and Eames, 2006, Athanasakou et al., 2009). Additionally, we find that owner analysts' recommendation upgrades underperform those of their peers by 0.8% in the two-month period after the announcement of the upgrades. Propensity score matching tests confirm these findings.

We contribute to the academic literature in at least three different ways. First, no one before us has examined the effect of the brokerage houses' ownership on their analysts' forecasts and recommendations. Given that employers' ownership in the followed firms create a serious conflict of interest (SEC, 2010), this topic is relevant and important to understand analyst behavior. Second, we contribute to the literature showing that institutional and block owners possess private information and through their activities reflect private information into prices (Edmans, 2009). Third, our results suggest that there probably are some levels of "information exchanges" between the asset management or trading unit and the equity research unit, and also subsidiaries in a banking conglomerate, similar to what happens in other firms.

Our study is closely related to the contentious strand of literature about investment banks' proprietary trading around their analyst recommendations. For example, some studies show that investment banks and their affiliates follow their analysts' recommendations (Chan et al., 2009, Jordan et al., 2012). On the contrary, Charitou and Karamanou (2020) find that

investment banks trade ahead of and against their analysts' recommendation changes in violation of existing regulations. Specifically, FINRA prohibits the analyst's employer from trading in the subject firm's stock and its derivatives based on non-public information of a report's content or publication timing. Moreover, Section 619 of the 2010 Dodd–Frank Wall Street Reform and Consumer Protection Act (nicknamed Volcker rule) prohibit proprietary trading that creates material conflicts of interest. However, banks were granted delays in compliance with the Volcker rule, and in 2017, U.S. President Donald Trump ordered a review of financial regulations, which results in a proposed revamp of the rule which has been approved by several regulatory agencies. These results cast doubt on the effectiveness of financial regulations put into place since the Global Analyst Research Settlements.

In one respect, our study adds to the debate and contribute to future evolution of regulations around proprietary trading and research department activities. In another respect, we shift the focus of regulations and research from trading to ownership, as it may jeopardize the integrity of the analyst reports. Additionally, while the regulations require disclosure based on one percent of ownership, absolute value of ownership can be a more relevant threshold. Higher value of investment makes owners more motivated to act partially. As a practical example, a 0.1% ownership in Amazon is worth about $1 billion, much more valuable and worth acting on than a 100% ownership in a $10-million company.

The rest of the paper is structured as follows: Section 3.2 reviews the literature; Section 3.3 develops hypotheses, methodology and variable construction; Section 3.4 describes the data and presents selected results; Section 3.5 concludes.

3.2 Literature review and hypotheses

There exists a large literature on the conflicts of interest that affect stock analysts. To structure this short survey we use the four categories identified by the SEC (2010) and already

listed in the introduction of this paper: investment banking relationships, brokerage commissions, analyst compensation, and ownership interest in the company.

For all of these categories there exists empirical evidence. Regarding banking relationships, brokerage houses have been shown to pressure their analysts to publish optimistic reports in order to solicit or maintain potential or existing business relationships with the followed firms. For example, Lin and McNichols (1998) demonstrate that analysts affiliated with underwriters issue more favorable growth forecasts and recommendations. Underwriter analysts appear to strategically revise target prices and recommendations to support stock price or benefit the investors of the followed firms (James and Karceski, 2006, Kolasinski and Kothari, 2008, Dechow et al., 2000, O'Brien et al., 2005).

Concerning brokerage commission, Irvine (2004) finds that analysts' buy and strong buy recommendations generate significantly more trading, and thus trading commission, for their employers. Developing on this point, Cowen et al. (2006) show that brokerage firms whose research is funded by trading commission are more optimistic in their forecasts and recommendations than others.

Moreover, analysts can be made partial by compensation and career concerns. Hong and Kubik (2003) find that optimistic analysts who help promoting stocks are rewarded in their career prospect. Groysberg et al. (2011) examine proprietary compensation data from two high-status banks and conclude that analyst compensation is designed to encourage actions that promote banking revenues.

Nevertheless, research on potential effect of ownership in the company is rare. Prior studies have looked at personal ownership of equity by the analysts themselves in the followed firms (Chan et al., 2018), but no one has looked at ownership of the analyst's employers. Other studies indicate that institutional owners usually have optimistic opinions about the stocks they own, and to some extent try to impose their views on others. Specifically, Gu et al. (2013) and

Firth et al. (2013) show that mutual funds pressure brokerage analysts through allocation of trading commission fees to issue optimistic recommendations for the stocks in which the funds have taken large positions. Firth et al. (2013) show that analysts are less likely to incorporate bad news in their recommendations for the stocks the funds own.

However, it is not straightforward why brokers are optimistic about their investments. Most likely because the effects of such investments on the owner's book. In order to account for equity investments, firms in the U.S. use two accounting standards: the U.S. GAAP and the IFRS. Specifically, if the equity investment is insignificant (usually less than 20% ownership in the investee), it is classified as either available-for-sale investment, held-for-trading investment, or investment designated at fair value, all of which must be carried at fair value. For significant non-controlling ownership, usually between 20 percent and 50 percent, FASB ASC 323 and IAS 28 require the investment to be recorded using the equity method. Under the equity method, the investment is carried at cost, but must be periodically reviewed and must be impaired following a decline in the stock's market value to below carrying value if the decline is deemed to be permanent. Such impairment losses are not allowed to be reversed even if the stock's market price increases in the future. If the ownership is controlling, usually above 50 percent, financial statements are consolidated following FASB ASC 805 and 810, or IFRS 10. In either cases where the investment is significant or controlling, the investee becomes an affiliate or a subsidiary of the owner. Prior research has found significant positive correlations between the parent and its affiliates and subsidiaries (Anginer et al., 2017). Therefore, the brokerage house owners may be induced to support the investee's stock price through optimistic opinions in their analysts' reports.

Following this argument, we conjecture that analysts are more optimistic if their employers are owners of the followed stocks. We propose the following hypothesis.

H1: Stock analysts are more optimistic than their peers if their employers own a stake in the subject firm.

Moreover, if owner analysts are strategically optimistic in order to support the performance of their employers' equity investment, they would do so more often in the time when support is needed most. We conjecture that in a time of market downturn, the differential optimism between owner analysts and non-owner analysts will be wider.

H2: The differential optimism between owner analysts and non-owner analysts is wider in times of market downturn.

We run the following regression to test our hypotheses:

$$Forecast\ Accuracy/Optimism = \beta_{0i} + \sum \beta_{mi} OWN_{mi} + \sum \beta_{ni} Control_{ni} + \varepsilon_i \quad (1)$$

Where OWN indicates ownership of the analyst's employer in the followed firm. Control variables include firm characteristics, analyst characteristics, firm fixed effects, year fixed effects, and analyst fixed effects.

3.3 Data and variable construction

3.3.1 Data

We use earnings forecasts, target prices and recommendations from the I/B/E/S database. Company financials are from Compustat. Ownership is from the Thomson-Reuters 13F Database and stock returns are from CRSP.

In order to test our hypotheses, we need to match owners in the 13F data with brokerage houses in I/B/E/S. Unfortunately, there is no common identifier of brokerage houses between these two files. We use the following procedure to match these two databases. Our approach is similar to that of Bodnaruk et al. (2009).

First, we decode the brokerage houses in I/B/E/S to actual names. Each house may be a stand-alone enterprise or belong to a financial conglomerate. Second, we try to find all subsidiaries and direct parent of each financial conglomerate in the 13F database in each year and sum up all their holdings in each stock at each report date. We then merge this aggregate number of holding of the conglomerate to the respective brokerage houses in I/B/E/S files to be used as the main independent variable of interest.

Decode brokerage houses in I/B/E/S to actual names

In order to decode analysts' employer codes, we use analyst names in I/B/E/S target price file and recommendation file. In these files, the brokerage house codes are abbreviations of the brokers' names. For example, the three brokers that provided the highest number of target prices are coded "MERRILL" (68,022 observations), "GOLDMAN" (67,526 observations), and "SMITH" (67,077 observations). As "MERRILL" and "GOLDMAN" can be easily guessed to be Merrill Lynch and Goldman Sachs, although we follow the same procedure to decode them, it is not interesting to be demonstrated here. Instead, we will demonstrate how we find out which broker "SMITH" represents.

We tabulate analyst names associated with a broker in the latest year where data are available, in this case 2016. We find 99 analysts are associated broker "SMITH" in 2016, representing 4,227 target prices. We choose the analysts whose names are not so common and whose numbers of forecasts are the large and search them on the internet, mainly tipranks.com and LinkedIn, for their profile. In the case of broker "SMITH" we look at the following names.

"M Bilerman": Search results show an equity analyst Michael Bilerman working for Citigroup in 2016. "S Gruber": An equity analyst Scott Gruber working for Citigroup in 2016. "P Juvekar": An equity analyst PJ Juvekar working for Citigroup in 2016. "K McShane, CFA":

An equity analyst Kate McShane, a CFA charter-holder, working for Citigroup in 2016. "G Badishkanian": An equity analyst Gregory Badishkanian working for Citigroup in 2016, etc.

Based on these searches, we assume that "SMITH" represents Citigroup[3]. We repeat this procedure for 149 brokers, accounting for about 95% of all observations in the target price file and recommendation file. Because the earnings forecast file does not contain analyst names, and contains a brokerage house code that is different from that in the recommendation file and target price file, we cannot decode the brokerage houses in this file directly. We match the brokerage houses in the price forecast file with the brokerage houses in the 1-year earnings forecast file using analyst codes in each month. The decoded brokerage houses account for 52.7% of the original earnings forecasts.

Find all subsidiaries of the brokerage houses and aggregate their ownership

We manually search the internet for the names of all subsidiaries or controlling entities of the financial groups related to the 149 brokerage houses decoded from I/E/B/S, mostly on google, Edgar database and company websites. In the case of Citigroup, we can find both its SEC filing list of subsidiaries and google search by keyword "Citigroup subsidiaries" also results in more than fifty names.

We search each of these names in the 13F data using the variables containing the owners' names and websites. If either the name matches or the website link directs to a website belonging to Citigroup or exhibiting Citigroup logo, we search for the owner's profile, mainly on Bloomberg and the company website, and news to identify the time the owner is acquired or separated from Citigroup. For example, Travelers was acquired by Citi in 1998 and was spun off in 2002. Thus, Travelers equity investments from 1998 to 2002 are considered as ownership

[3] We do not know why "SMITH" represents Citigroup. One explanation can be of historical reason. Citigroup previously owned a brokerage house called "Smith Barney". In 2009, it is sold to Morgan Stanley and subsequently renamed "Morgan Stanley Wealth Management".

by Citigroup, but separated from Citigroup after 2002. In the appendix, we present the list of 109 Citigroup subsidiaries found in the 13F data. Because each Citigroup subsidiary appears as a separate owner in 13F data, we sum up their reported ownership each quarter to have all of Citigroup's holdings in a given firm, and merge these aggregate values back to I/B/E/S files.

We successfully find in the 13F data subsidiaries related to 93 out of the decoded 149 brokerage houses from I/B/E/S. Obviously, our matching procedure is not perfect. Matching errors can come from manually decoding the brokerage houses and manually find the subsidiaries in 13F files.

Table 1 presents summary statistics of ownership by analysts' employers in followed firms' stocks reported at the end of the quarter when recommendations are issued. Column (1) shows holdings for the full sample. Column (2) and (3) show holdings reported after buy recommendations and sell/hold recommendations. Ownership of followed stock varies largely from zero to billions of USD. Mean ownership is substantially higher than median, suggesting that there exist some extremely large holdings.

Table 1: Statistics of analysts' employers' ownership in the followed firms reported at the end of the quarter when a recommendation is issued

	Total holding (USD)		
	(1)	(2)	(3)
Percentiles	Full	Buy	Hold/Sell
1%	0	0	0
5%	47	1,414	0
10%	38,792	48,875	31,049
25%	478,778.5	498,862	462,577
50%	3,482,525	3,582,392	3,404,540
75%	2.19E+07	2.33E+07	2.07E+07
90%	9.41E+07	1.05E+08	8.69E+07
95%	2.18E+08	2.45E+08	1.95E+08
99%	8.24E+08	9.25E+08	7.40E+08
Mean	4.88E+07	5.40E+07	4.44E+07
Std. Dev.	2.01E+08	2.15E+08	1.89E+08
No. Obs.	187,936	86,774	101,162

3.3.2 Variables

Forecasts and recommendations

As defined in the dataset, recommendations are coded to with integers from 1 to 5 corresponding to strong buy, buy, hold, sell, and strong sell recommendation, respectively. Given that it is easier to read the results if higher value is associated with higher optimism, we invert these codes. We recode recommendations by creating the variable *RECOM*, which still has integer values from 1 to 5, but with 1 now corresponding to strong sell, 2 to sell etc. We scale all recommendations by the range of recommendations of all analysts for each firm in each year. By construction, this variable has its value ranging from zero to one with higher values indicating more favorable recommendations.

$$R\_RECOM = \frac{RECOM - \min(RECOM)}{max(RECOM) - \min(RECOM)} \quad (1)$$

An analyst is considered to be optimistic if his recommendation is more favorable than those of his peers. We use a relative measure of recommendation optimism. Following prior studies, recommendation optimism (*RECOPT*) of an analyst for a firm is measured relative to the mean of recommendations by all analysts for the firm in the last 180 days prior to the day before the recommendation announcement (Gu et al., 2013, Firth et al., 2013).

$$RECOPT = RECOM - mean(RECOM) \quad (2)$$

We also scale *RECOPT* across all analysts for a firm in a year.

$$R\_RECOPT = \frac{RECOPT - \min(RECOPT)}{max(RECOPT) - \min(RECOPT)} \quad (3)$$

Most intuitively, target price accuracy can be measured by the distance between target price and actual market price at the end of forecast horizon. As we keep only target prices with a 12-month forecast horizon, we measure target price accuracy and optimism relative to the realized stock price 365 days after the target is announced (P_{12}). This measure is consistent

with prior studies on target prices (Bilinski et al., 2012, Bradshaw et al., 2013, Chan et al., 2018). If the market price at exactly 365 days ahead is not available, we substitute it with the use the last available market price in up to ten days. We define the target price absolute forecast error (*TPAFE*) and target price optimism (*TPOPT*) as:

$$TPAFE = |TP - P_{12}| \quad (5)$$

$$TPOPT = TP - P_{12} \quad (6)$$

Following Chan et al. (2018), we scale each target price error and optimism by the range of target prices errors and optimism of all analysts for the firm in the year, as in equation (5) and (6) respectively. This procedure results in two variables ranging from zero to one, relative target price accuracy (*TPACCUR*) and relative target price optimism *R_TPOPT*, with higher values indicating higher accuracy and optimism.

$$TPACCUR = \frac{max(TPAFE) - TPAFE}{max(TPAFE) - min(TPAFE)} \quad (4)$$

$$R\_TPOPT = \frac{TPOPT - \min(TPAFE)}{max(TPOPT) - \min\,(TPOPT)} \quad (5)$$

Intuitively, users of an analysis report would probably judge the performance of an earnings forecast primarily by how far the forecast is from the actual accounting earnings. Hence, we define absolute forecast error (*AFE)* as the distance between actual earnings and forecasted earnings (Jacob, 1997, Mikhail et al., 1997, Mikhail et al., 2003, Drake and Myers, 2011).

$$AFE = \left|E_{forecast} - E_{actual}\right| \quad (6)$$

$$OPT = E_{forecast} - E_{actual} \quad (7)$$

Jacob et al. (1999) criticize the use of absolute forecast errors for being contaminated by inter-temporal changes and cross-sectional differences. Following Clement and Tse (2005), we derive a relative measure of forecast accuracy (*ACCUR*). Across all analysts, we subtract

the maximum absolute forecast error and optimism for a firm in a year by absolute forecast error of each analyst for the same firm, and scale it by the range of absolute forecast errors and optimism. By construction, this variable has a continuous value range from zero to one. The higher this variable, the more accurate or optimistic the forecast.

$$ACCUR = \frac{max(AFE) - AFE}{max(AFE) - min(AFE)} \quad (8)$$

$$R\_OPT = \frac{OPT - \min(OPT)}{max(OPT) - min(OPT)} \quad (9)$$

Cumulative abnormal returns

We calculate cumulative abnormal returns (CARs) around recommendation announcements using daily returns from CRSP. $CAR_{it}[u; v]$ is the cumulative return of stock i from day t+u to day t+v around the recommendation announcement date t, minus the cumulative value-weighted market return in the same window.

$$CAR_{it}[u;v] = \left(\prod_{j=u}^{v}(1 + R_{ij})\right)^{\frac{1}{v-u}} - \left(\prod_{j=u}^{v}(1 + R_{Mj})\right)^{\frac{1}{v-u}} \quad (10)$$

Where R_{ij} is daily return of stock i on day j, R_{Mj} is daily value-weighted market return on day j.

Ownership

Our main independent variables of interest measure ownership of the analyst's employer in the followed firm reported quarterly. We use variable *OWN* to indicate holding in the followed firm. *OWN* is a dummy variable taking the value of one if the analyst's employer owns a stake valued at least $1 million in the followed firm's stock during the quarter when the forecast or recommendation is announced or up to two quarters before, and zero otherwise. The $1-million threshold is arbitrarily chosen, as we think that the holding must provide

economic incentives large enough for the analyst to sacrifice his/her objectivity. Robustness tests confirm that choosing different value thresholds gives quantitatively similar results.

Control variables

We consult the literature to add relevant control variables into our models. Mikhail et al. (1997), followed by many other studies, suggest that analysts' individual characteristics, could potentially affect forecast accuracy. *GEXPER* is the analyst's general experience, measured by the number of years the analyst has been in our data to the day of the forecast. *FEXPER* is the analyst's firm-specific experience, measured by the number of years the analyst has covered the followed firm in our data to the day of the forecast. *NIND* is the number of 2-digit SIC code industries an analyst covers in a given year. *NFIRM* is the number of firms an analyst covers in a given year. Lower *GEXPER*, *FEXPER*, and higher *NFIRM*, *NIND* may be associated with higher forecast errors (Mikhail et al., 1997, Mikhail et al., 2003, Clement and Tse, 2005). *BSIZE* is bank size, calculated as the number of analysts working for the bank in a given year as observed in the dataset. Larger brokerage house may be able to make more accurate forecasts because they can attract more talented employees and have more resources. *FREQ* is the number of earnings forecast revisions the analyst issues for a firm in a year. *FREQ* represents analyst efforts. Higher *FREQ* is expected to improve forecast accuracy. *FCAGE* is the number of days from earnings forecast announcement date to announcement of actual earnings. More distant forecasts bear more uncertainty, thus are less accurate.

Following prior studies (Clement and Tse, 2005, Chan et al., 2018), analyst characteristics are scaled using the same procedure used for the dependent variables. For each firm each year, an analyst characteristics X is scaled relative to all analysts who issue a forecast for that firm in that year.

$$R_X = \frac{X - \min(X)}{max(X) - \min(X)} \quad (11)$$

Table 2: Variable definitions

Variable	Definition
Dependent variables	
CAR[u;v]	cumulative abnormal returns of the followed stock from day v to day v around announcement of recommendation change.
ACCUR	earnings forecast accuracy.
R_OPT	is earnings forecast optimism.
TPACCUR	is target price accuracy.
R_TPOPT	is target price optimism.
R_RECOM	is recommendation.
R_RECOPT	is recommendation optimism.
Independent variables	
OWN	equals one if the analyst's employer financial group reports a holding of at least one million USD worth of the followed firm's stock in the current quarter or two quarter before the current quarter, and zero otherwise.
RECOM	is recommendation code. RECOM equals 1, 2, 3, 4, 5 if recommendation is strong buy, buy, hold, sell, strong sell, respectively.
GEXPE	is the number of years from the year the analyst first appears in I/B/E/S earnings forecast file to the current year.
FEXPE	is the number of years from the year the analyst first issues an earnings forecast for the followed firm to the current year.
BSIZE	is the number of analysts in I/B/E/S earnings forecast file that belong to the same brokerage house in the year.
UNDER	equals one if the analyst's employer has underwritten the followed firm's equity issue during the past 5 years and zero otherwise.
NFIRM	is the number of firms the analyst follows in the current year as in I/B/E/S earnings forecast file.
NIND	is the number of 2-digit SIC code industry the analyst follows in the current year as in I/B/E/S earnings forecast file.
FREQ	is the number of earnings forecast revisions the analyst makes for the followed firm in the current year.
FIRMAGE	is the followed firm's age, calculated from COMPUSTAT.
FOLLOW	is the number of analysts who follow the firm in the current year.
BM	is the followed firm's book-to-market ratio.
ROA	is the followed firm's return-on-assets.
LEV	is the followed firm's leverage.
MV	is the followed firm's market capitalization.

We also account for firm-specific factors that may affect analyst forecasts, including book-to-market ratio (*BM*), profitability (*ROA*), leverage (*LEV*) and market capitalization (*MV*). *FOLLOW* is information intensity or analyst competition surrounding a given firm, measured by the number of analysts covering that firm in a given year. Following prior studies, for an analyst in a given year, firm characteristics are scaled across all firms for which the analyst issues a forecast in that year using equation (11) above.

In order to control for other potential biases, we also add year fixed effects, firm fixed effects, and analyst fixed effects. Table 2 presents variable definitions in detail.

3.4 Results

3.4.1 Summary statistics

Table 3 presents summary statistics of key variables matched into the recommendation file, unscaled and sorted into ownership groups. Mean *OWN* indicates that 26.3% of recommendations are made by analysts whose employers own at least $1 million worth of the followed stocks in the quarter forecasts are made or two quarter before, suggesting that ownership by brokerage houses in the followed firms is a widespread phenomenon.

Earnings forecast accuracy (*ACCUR*) is higher in the group of owner analysts. This may be consistent with the hypothesis that owners provide analysts with more informational resources. Nevertheless, it can also be explained by other variables. Specifically, owner analysts belong to significantly larger investment banks (as evidenced by *BSIZE*), which are also more likely to have an underwriting relationship with the followed firms (*UNDER*). Moreover, owner analysts are more experienced (*GEXPER*), cover the followed firms longer (*FEXPER*), follow fewer industries (*NIND*), and put more efforts in the stocks their employers own (*FREQ*). All of these factors can contribute to superior forecast accuracy of owner analysts.

Table 3: Summary statistics

This table presents summary statistics of variables match into Recommendation file which is used for the regressions in Table 4. Note that the values presented here are not scaled. Column (1), (2), (3) respectively present statistics for the groups of non-owner, owner, and all analyst recommendations.

	(1) OWN=0		(2) OWN=1		(3) Full sample	
	Mean	Obs.	Mean	Obs.	Mean	Obs.
OWN	0	479,228	1	171,018	0.263	650,246
CAR[-1;+1]	-0.002	318,483	-0.003	156,576	-0.003	475,059
CAR[-1;+3]	-0.002	318,396	-0.003	156,539	-0.002	474,935
CAR[+2;+63]	0.011	319,178	0.011	156,848	0.011	476,026
RECOM	3.672	479,228	3.522	171,018	3.633	650,246
UPGRD	0.170	479,228	0.158	171,018	0.167	650,246
DOWNGRD	0.194	479,228	0.177	171,018	0.190	650,246
ACCUR	0.682	266,698	0.725	56,962	0.690	323,660
GEXPE	8.613	275,063	10.33	57,481	8.910	332,544
FEXPE	2.078	275,063	2.906	57,481	2.222	332,544
BSIZE	33.72	275,063	74	57,481	40.69	332,544
UNDER	0.078	479,228	0.164	171,018	0.101	650,246
NFIRM	14.5	275,063	14.49	57,481	14.5	332,544
NIND	3.234	200,803	2.879	53,468	3.159	254,271
FREQ	3.71	275,063	4.2	57,481	3.795	332,544
FIRMAGE	16.61	213,427	21.84	56,370	17.7	269,797
FOLLOW	14.65	275,063	18.98	57,481	15.4	332,544
BM	0.442	187,036	0.441	49,022	0.442	236,058
ROA	0.042	177,386	0.073	48,662	0.048	226,048
LEV	0.525	200,056	0.567	53,308	0.534	253,364
MV	7.302	187,301	8.423	49,167	7.535	236,468

Regarding the firms owned, they are followed by more analysts, they are larger in size (*MV*) and more profitable (*ROA*). Mean *RECOM* is 3.67, indicating that there are more buy than sell recommendations, which is in line with prior literature.

Following Chan et al. (2018), recommendation upgrades and downgrades (*UPGRD* and *DOWNGRD*) respectively equal one if the analyst issues a new recommendation that is more and less favorable than the one which he/she has made within the last 366 days and zero otherwise. There are more downgrades than upgrades. Compared to non-owner analysts, owner analysts are less likely to make recommendation changes.

3.4.2 Owner analysts' recommendation optimism

Table 4 tests the relationship between analyst recommendation optimism and ownership of the analysts' employers in the followed firms. The dependent variable in regression (1) is the scaled recommendation. The dependent variable in regression (2) is scaled recommendation optimism. Recommendation optimism is measured relative to mean recommendations announced 180 days before announcement day for the same stock. We control for firm characteristics, analyst characteristics, year fixed effects, firm fixed effects, and analyst fixed effects. Standard errors are clustered at the firm level.

The coefficient of *OWN* in regression (1) is positive and statistically significant, suggesting that analysts are more optimistic if their employers own the followed firms' stocks. The coefficient of *OWN* in regression (2) is also positive and highly significant, indicating that owner analysts are statistically more favorable in their recommendations compared to the market consensus. This is consistent with our first hypothesis that owner analysts are optimistic about their employers' equity investments.

Optimism in earnings forecasts (*R_OPT*) also has a significant positive relationship with recommendation optimism. Analysts working at equity underwriting houses are particularly optimistic in their recommendations. This is a fact well-known in the literature. Firm-specific experience seems to reduce optimism in recommendations. The size of the brokerage house also alleviates optimism. Analysts following more industries are more optimistic, whereas analysts following more firms are less optimistic.

Regarding firm characteristics, larger firms and firms followed by more analysts are more likely to receive overoptimistic recommendations, whereas, firms with higher book-to-market ratios receive less optimistic recommendations.

Table 4: Owner analysts' recommendation optimism

This table presents tests of the relationship between recommendation optimism and ownership of the analyst's employer in the followed firm. Column (1) and (2) are estimated using pooled OLS models. Standard errors are clustered by firms. Prefix "R_" in variable names indicates scaled variables using the procedure described in Section 3. See Table 2 for variable definitions. t-statistics in parentheses. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	(1)	(2)
VARIABLES	R_RECOM	R_RECOPT
OWN	0.0117***	0.0113***
	(3.869)	(3.599)
R_OPT	0.0418***	0.0320***
	(13.62)	(8.484)
R_GEXPE	-0.0132	0.00805
	(-1.433)	(0.655)
R_FEXPE	-0.0270***	-0.0154***
	(-9.777)	(-5.213)
R_BSIZE	-0.0474***	-0.0535***
	(-7.995)	(-7.763)
UNDER	0.0268***	0.0181***
	(4.680)	(2.696)
R_NFIRM	-0.0283***	-0.0329***
	(-5.223)	(-5.868)
R_NIND	0.00309	0.0117**
	(0.679)	(2.111)
R_FREQ	0.00989***	0.0102***
	(2.897)	(2.885)
R_FIRMAGE	-0.00844	-0.0110**
	(-1.473)	(-2.139)
R_FOLLOW	0.0178***	0.0163***
	(3.872)	(3.490)
R_BM	-0.00870**	-0.000193
	(-2.518)	(-0.0555)
R_ROA	0.00191	-0.00476
	(0.464)	(-1.417)
R_LEV	0.00152	0.000739
	(0.339)	(0.197)
R_MV	0.0303***	0.0199***
	(5.867)	(3.926)
Constant	0.504***	0.499***
	(62.50)	(66.02)
Observations	172,963	136,221
Year FE	Yes	Yes
Firm FE	Yes	Yes
Analyst FE	Yes	Yes
Clustered SE	Firm	Firm

3.4.3 Owner analysts' target price forecast accuracy and optimism

Table 5 relates ownership of the analysts' employers in the followed firms with the analysts' target price accuracy and optimism. We control for several firm characteristics, analyst characteristics, year fixed effects, firm fixed effects, and analyst fixed effects. All variables except dummies are scaled using the procedure described in Section 3.

As indicated by the coefficient of *OWN* in Column (2), owner analysts are significantly more optimistic in their target prices. Column (1) reveals that their optimism results in less accurate target prices, as indicated by significant negative coefficient of *OWN*. That owner analysts are statistically more optimistic to the detriment of their accuracy confirms our conjectures that they are afflicted by ownership conflicts of interests. These findings are also in line with previous studies which find that owners in general prefer optimistic opinions about the stocks they own (Firth et al., 2013, Gu et al., 2013, Chan et al., 2018).

The coefficients of *ACCUR* and *R_OPT* are highly significant and positive. These results suggest that earnings forecasts may be used to justify target prices. Analysts at larger brokerage houses are less optimistic. Although target price accuracy is positively related with the size of brokerage houses, the coefficient is not statistically significant. Analysts affiliated with equity underwriters are significantly more optimistic in their target price, which is consistent with prior studies. More experienced analysts appear slightly less accurate, but this result is weakly significant. Analysts covering more industries also seem to be more optimistic.

For firms that are followed by more analysts, target prices are more accurate and less optimistic. This may be due to analyst competition or information intensity. Target prices for firms with higher market capitalization, higher bool-to-market ratios, higher profitability and high leverage seem more optimistic.

Table 5: Owner analysts' target price accuracy and optimism

This table presents tests of the relationship between target price accuracy, optimism and ownership of the analyst's employer in the followed firm. Column (1) and (2) are estimated using pooled OLS models. Standard errors are clustered by firms. Prefix "R_" in the variable names indicates scaled variables using the procedure described in Section 3. See Table 2 for variable definitions. t-statistics in parentheses. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	(1)	(2)
VARIABLES	TPACCUR	R_TPOPT
OWN	-0.00473**	0.0162***
	(-2.155)	(7.268)
ACCUR	0.0137***	
	(4.755)	
R_OPT		0.0326***
		(12.06)
R_GEXPE	-0.0230**	0.00627
	(-2.344)	(0.657)
R_FEXPE	-0.00482*	0.00409
	(-1.707)	(1.485)
R_BSIZE	0.00593	-0.0208***
	(0.936)	(-3.409)
UNDER	0.00202	0.0104***
	(0.621)	(3.156)
R_NFIRM	-0.00554	-0.00451
	(-1.115)	(-0.964)
R_NIND	0.00490	0.00598
	(1.199)	(1.464)
R_FREQ	-0.00218	0.00663**
	(-0.751)	(2.422)
R_FIRMAGE	0.00373	0.00139
	(0.698)	(0.255)
R_FOLLOW	0.0168***	-0.00701
	(3.147)	(-1.410)
R_BM	-0.00632	0.00647*
	(-1.575)	(1.662)
R_ROA	-0.00475	0.00664*
	(-1.288)	(1.806)
R_LEV	-0.0119**	0.0118***
	(-2.398)	(2.610)
R_MV	0.0105*	0.0102**
	(1.959)	(1.969)
Constant	0.581***	0.462***
	(75.37)	(63.94)
Observations	237,647	237,785
Year FE	Yes	Yes
Firm FE	Yes	Yes

VARIABLES	(1) TPACCUR	(2) R_TPOPT
Analyst FE	Yes	Yes
Clustered SE	Firm	Firm

3.4.4 Owner analysts' earnings forecast accuracy and optimism

In Table 6, we test the effect of brokerage houses' ownership on their analysts' earnings forecasts. The dependent variable in column (1) is earnings forecast accuracy, and in column (2) earnings forecast optimism. The dependent variable *OWNY* is defined slightly different from earlier sections. As we use annual earnings forecasts, *OWNY* equals one if at least one-million-dollar worth ownership is reported anytime during the calendar year and zero otherwise. The coefficients of *OWNY* are statistically insignificant in these regressions.

Prior accounting studies find that stock returns are higher if the firm's actual earnings exceed expectations (Bartov et al., 2002). These positive surprises can be achieved by analysts, in collusion with firm management, if they issue slightly pessimistic, beatable forecasts to guide investors' expectation. Beatable forecasts are relatively precise, but slightly pessimistic so that the management can achieve marginal positive earnings surprises (Burgstahler and Eames, 2006, Bartov et al., 2002, Athanasakou et al., 2009, Athanasakou et al., 2011).

Because owner analysts are more likely to have private contacts with management of the firms, following the literature on forecast management, we assume they have the incentive to issue beatable forecasts to support the followed firms' management and stock prices. We define beatable forecasts (*SUSPECT*) as those lower than realized earnings by less than 10 cent of a dollar.

Table 6: Owner analysts' earnings forecast accuracy and optimism

This table presents tests of the relationship between earnings forecast accuracy, optimism and ownership of the analyst's employer in the followed firm using pooled OLS regressions. Prefix "R_" in variable names indicate scaled variables using the procedure described in Section 3. See Table 2 for variable definitions. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	(1)	(2)
VARIABLES	ACCUR	R_OPT
OWNY	0.00225	0.000539
	(0.916)	(0.188)
Lag(ACCUR)	0.0209***	
	(6.432)	
Lag(R_OPT)		0.0306***
		(7.474)
R_GEXPE	-0.00803	-0.00992
	(-0.938)	(-1.015)
R_FEXPE	-0.00193	0.00224
	(-0.685)	(0.681)
R_BSIZE	0.000140	-0.00818
	(0.0267)	(-1.325)
UNDER	9.90e-05	-0.00226
	(0.0303)	(-0.600)
R_NFIRM	0.0170***	0.00791
	(3.798)	(1.303)
R_NIND	-0.00637*	0.00629
	(-1.668)	(1.315)
R_FREQ	0.0808***	-0.0161***
	(24.02)	(-3.910)
R_FIRMAGE	-0.0151***	-0.00417
	(-2.874)	(-0.635)
R_FOLLOW	0.0811***	-0.0455***
	(15.31)	(-6.100)
R_BM	0.000782	-0.0371***
	(0.213)	(-7.293)
R_ROA	-0.000450	0.0236***
	(-0.129)	(4.662)
R_LEV	-0.00107	-0.0176***
	(-0.267)	(-2.868)
R_MV	-0.000975	0.0239***
	(-0.195)	(3.531)
R_FCAGE	-0.277***	0.0337***
	(-66.73)	(7.037)
Constant	0.697***	0.518***
	(90.21)	(56.77)
Observations	231,247	231,414
Year FE	Yes	Yes

	(1)	(2)
VARIABLES	ACCUR	R_OPT
Firm FE	Yes	Yes
Analyst FE	Yes	Yes
Clustered SE	Firm	Firm

Because the dependent variable is a dummy, we use random effects probit regressions in column (1). Unreported rho (ρ) is different from zero, suggesting that the proportion of the total variance contributed by the panel-level variance component is important and thus pooled estimator is biased. Column (1) indicates that owner analysts are significant more likely to issue beatable forecasts, hinting at their closer relationship to the followed firms' management or private information.

Note that this specification of the random effect probit model is not consistent with previous regressions because the probit model does not allow fixed effects, whereas we have high levels of fixed effects in our data (about 4,800 firms, 8,600 analysts, 18 years) that make it difficult to apply other equivalent logistic models. As long as we care about the signs of the regression coefficients, OLS has been used in previous studies (Horrace and Oaxaca, 2006). In column (2), we fit the regression using OLS with all the fixed effects used previously. In this specification, the coefficient of ownership is still statistically significant significant, albeit weaker.

In summary, Table 7 suggests that owner analysts may have better access to the management of the followed firms. Despite this privilege, they seem to be making more optimistic forecasts and recommendations, to the detriment of their accuracy.

Table 7: Owner analysts' suspected earnings forecasts

This table presents tests of the relationship between suspected earnings forecasts and ownership of the analyst's employer in the followed firm. Column (1) is estimated using a random effects probit model. Column (2) is estimated using an OLS model. Prefix "R_" in variable names indicate scaled variables using the procedure described in Section 3. See Table 2 for variable definitions. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

VARIABLES	(1) SUSPECT	(2) SUSPECT
OWNY	0.0616***	0.00820**
	(6.164)	(2.074)
lag(ACCUR)	0.0924***	0.00668
	(5.944)	(1.418)
R_GEXPE	0.0141	0.00481
	(1.084)	(0.371)
R_FEXPE	-0.0569***	0.00335
	(-3.197)	(0.761)
R_BSIZE	-0.0562***	-0.00456
	(-4.462)	(-0.582)
UNDER	-0.00870	0.00606
	(-0.461)	(1.175)
R_NFIRM	0.0529***	0.0122
	(2.899)	(1.608)
R_NIND	-0.0279	-0.00243
	(-1.604)	(-0.381)
R_FREQ	0.255***	0.0701***
	(15.14)	(13.18)
R_FIRMAGE	-0.000685	0.00225
	(-0.0212)	(0.270)
R_FOLLOW	0.000272	-0.0325***
	(0.00832)	(-3.159)
R_BM	-0.258***	-0.0403***
	(-10.89)	(-5.779)
R_ROA	0.145***	0.0310***
	(6.883)	(4.623)
R_LEV	-0.210***	-0.0265***
	(-7.932)	(-3.196)
R_MV	0.0742**	-0.00608
	(2.322)	(-0.706)
RFCAGE	-0.381***	-0.115***
	(-20.41)	(-19.62)
Constant	-0.287***	0.418***
	(-8.360)	(34.26)
Observations	232,854	231,704
Year FE		Yes
Firm FE		Yes

VARIABLES	(1) SUSPECT	(2) SUSPECT
Analyst FE		Yes
Clustered SE	Firm	Firm

3.4.5 Market reactions to owner analysts' recommendation changes

Table 8 present market reactions to owner analysts' recommendation changes around announcement days. Recommendation changes are sorted into upgrades and downgrades. The independent variable of interest is *OWN*, which equals one if the analyst's employer owns at least $1 million value of stock in the followed firm in the same quarter the recommendation revision is made or in the two previous quarters. We report cumulative abnormal returns of the firm's stock in two short-term windows immediately around the event days, namely three days (from day t-1 to day t+1) and five days (from day t-1 to day t+3) in column (1) to (4). The coefficients of *OWN* observed in column (1) to (4) are all insignificant, suggesting that investors may be aware of owner analyst bias and do not consider their recommendation changes as more informative.

In column (5) and (6), we examine the performance of owner analyst recommendation changes in a two-month window (from day t+2 to t+63). The coefficient of *OWN* in upgrades regression is negative, and statistically significant, albeit weakly, suggesting that owner analysts' recommendation upgrades underperform those of their peers by 0.8% in two months. This again indicates that owner analysts are over-optimistic in their recommendations.

Table 8: Market reactions to owner analysts' recommendation changes

This table presents market reactions, denoted by cumulative abnormal stock returns, to owner analysts' recommendation changes. Column (1) to (4) presents market reaction in 3 days and 5 days windows around the announcement of the recommendation change. Column (5) and (6) show the performance of the recommendation change in two months after its announcement. Prefix "R_" in variable names indicate scaled variables using equation (10). See Table 2 for variable definitions. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	CAR[-1;1]	CAR[-1;1]	CAR[-1;3]	CAR[-1;3]	CAR[-2;63]	CAR[-2;63]
	Upgrades	Downgrades	Upgrades	Downgrades	Upgrades	Downgrades
OWN	-0.000746	-0.00333	-0.00152	-0.00252	-0.00806*	-0.00657
	(-0.397)	(-1.608)	(-0.701)	(-1.114)	(-1.785)	(-1.370)
ACCUR	-0.000542	-0.00406*	0.000547	-0.00340	0.00999*	-0.00395
	(-0.254)	(-1.896)	(0.237)	(-1.450)	(1.909)	(-0.760)
R_GEXPE	-0.0126	0.000654	-0.0141	-0.00185	0.0308*	-0.0357**
	(-0.982)	(0.0844)	(-0.849)	(-0.220)	(1.780)	(-2.002)
R_FEXPE	0.00300	0.00225	0.00174	0.00356	0.00755	-0.00116
	(1.175)	(0.960)	(0.579)	(1.432)	(1.466)	(-0.220)
R_BSIZE	0.00916*	-0.00904*	0.0102*	-0.0109**	0.0122	0.0181*
	(1.939)	(-1.810)	(1.933)	(-2.037)	(1.052)	(1.666)
UNDER	0.000718	-0.0128**	-0.00148	-0.0126**	0.0314***	0.0171
	(0.142)	(-2.382)	(-0.279)	(-2.190)	(3.104)	(1.339)
R_NFIRM	0.00250	-0.000187	0.00255	-0.000543	0.00659	0.00326
	(0.592)	(-0.0498)	(0.539)	(-0.134)	(0.706)	(0.372)
R_NIND	0.00230	0.00420	0.00118	0.00342	0.00806	0.00379
	(0.638)	(1.208)	(0.288)	(0.904)	(1.001)	(0.444)
R_FREQ	0.00408*	-0.00419*	0.00296	-0.00667***	0.00332	-0.00667
	(1.946)	(-1.784)	(1.237)	(-2.646)	(0.578)	(-1.153)
R_FIRMAGE	-0.00245	-0.00542	-0.00715	-0.00754	-0.00235	-0.0205*
	(-0.578)	(-1.136)	(-1.454)	(-1.493)	(-0.228)	(-1.849)
R_FOLLOW	-0.0228***	-0.0139***	-0.0254***	-0.0128***	-0.0825***	-0.0611***

VARIABLES	(1) CAR[-1;1]	(2) CAR[-1;1]	(3) CAR[-1;3]	(4) CAR[-1;3]	(5) CAR[-2;63]	(6) CAR[-2;63]
	Upgrades	Downgrades	Upgrades	Downgrades	Upgrades	Downgrades
	(-4.174)	(-3.437)	(-4.275)	(-2.944)	(-9.428)	(-6.280)
R_BM	-0.00118	-0.0285***	-0.00432	-0.0327***	-0.0637***	-0.0415***
	(-0.379)	(-8.376)	(-1.203)	(-8.930)	(-8.706)	(-5.597)
R_ROA	-0.00193	0.00305	-0.00358	0.00240	-0.000897	0.00911
	(-0.614)	(1.088)	(-0.956)	(0.789)	(-0.141)	(1.393)
R_LEV	0.00522	-0.0138***	0.00801*	-0.0155***	-0.0186**	-0.00946
	(1.355)	(-3.849)	(1.746)	(-3.898)	(-2.453)	(-1.171)
R_MV	0.00605	0.0227***	0.00814	0.0223***	0.0361***	0.0234**
	(1.116)	(5.341)	(1.359)	(4.838)	(3.734)	(2.440)
Constant	0.0387***	-0.0238***	0.0452***	-0.0195***	0.0474***	0.0732***
	(5.067)	(-3.819)	(4.737)	(-2.939)	(3.556)	(5.353)
Observations	30,851	32,260	30,851	32,260	30,857	32,269
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Analyst FE	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm

Table 8 also reveals other interesting findings. The coefficient of *ACCUR* in column (2) is negative and significant, but is positive and significant in column (5). This can be interpreted as downgrades by more accurate analysts being considered more informative and reflected constantly into stock prices, but their upgrades are not welcomed with as much enthusiasm and need longer time to be updated into price, possibly when information is confirmed as time passes.

More experienced analysts create larger market reactions with their recommendation changes, but the effect is not instant and takes a while to show up in the stock price. Both upgrades and downgrades by analysts who work for larger investment banks and those which have underwritten the firms' equity in the past five years are more informative. Analysts who put more effort in the followed firms also create larger market reactions upon their changes of recommendations. Downgrades made by analysts affiliated with underwriters create significantly larger market reactions, but upgrades do not, suggesting that investors do not believe in their upgrades more than their peers' upgrades.

3.4.6 Analyst forecast and the crises

Table 9 shows the effect of a bear market on owner analysts' behavior. *CRISIS* is a dummy variable taking the value of one if the announcement date of the target price is between June 1st 2000 and June 30th 2002, or between September 1st 2008 and March 30th 2009, and zero otherwise. This indicator of crisis times and its interaction with OWN are added into the two regressions in Table 4.

Understandably, in the time of market downturn, analysts are less optimistic on price forecasts, as indicated by the coefficient of *CRISIS* in column (2). This lower optimism seems to benefit forecast accuracy, as the coefficient of *CRISIS* is positive and highly significant in column (1). This is also consistent with Loh and Stulz (2018), who find that analysts are more

precise during bad times due to analyst increased competition and career concerns, which make them work harder.

Nevertheless, the interpretation of the interaction term (*OWN* x *CRISIS*) is less favorable for owner analysts. We know from previous sections that owner analysts are generally more optimistic and less accurate in their target price than their colleagues. But column (2) shows that in time of crisis, this difference in optimism between owner analysts and non-owner analysts is even wider, as indicated by the positive and highly significant coefficient of the interaction term. This result highlights the importance of the owner analysts' conflicts of interest in the time when objectivity is needed most. This result supports our second hypothesis.

Table 9: Owner analyst optimism in times of crisis

This table presents tests of the relationship between target price accuracy, optimism and ownership of the analyst's employer in the followed firm. Column (1) and (2) are estimated using pooled OLS models. See Table 2 for variable definitions. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	(1)	(2)
VARIABLES	TPACCUR	R_TPOPT
OWN	-0.00564**	0.0116***
	(-2.465)	(5.051)
CRISIS	0.0338***	-0.0729***
	(6.887)	(-14.68)
OWN x CRISIS	-0.00233	0.0272***
	(-0.419)	(5.024)
Observations	237,647	237,785
All Controls	Yes	Yes
Firm FE	Yes	Yes
Analyst FE	Yes	Yes
Clustered SE	Firm	Firm

3.4.7 Propensity score matching

In this part, we perform propensity score matching using the nearest neighborhood matching between owner analysts (treated group) and non-owner analysts (control group).

Matching variables are *R_OPT*, *R_GEXPE*, *R_FEXPE*, *R_BSIZE*, *R_NFIRM*, *R_NIND*, *R_FREQ*, *R_FIRMAGE*, *R_FOLLOW*, *R_BM*, *R_ROA*, *R_LEV*, *R_MV*, industries dummies and years dummies, and brokerage house dummies. We also apply the value for maximum propensity score distance of controls to be 0.01. The results of the tests are reported in Table 7. The average treatment effects on the treated (ATTs) of *R_RECOM*, *R_REOPT* and *R_TPOPT* are positive and highly significant, suggesting that owner analysts are much more optimistic than non-owner analysts. These results support our hypotheses.

Table 10: Propensity score matching

This table shows the average treatment effect based on propensity score matching using nearest neighborhood matching. The treatment group is analysts affiliated with debt underwriters. The control group is analysts affiliated with equity underwriters. Matching variables are R_OPT, R_GEXPE, R_FEXPE, R_BSIZE, R_NFIRM, R_NIND, R_FREQ, R_FIRMAGE, R_FOLLOW, R_BM, R_ROA, R_LEV, R_MV, industry dummies and year dummies, brokerage house dummies. t-statistic is shown in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels. See Section 3 and Table 2 for variable definitions.

	ATT (average effect of treatment on the treated)
R_RECOM	0.0252***
	(7.54)
RRECOPT	0.0189***
	(5.96)
RTPOPT	0.0182***
	(8.92)
TPACCUR	-0.001
	(-0.47)

3.5 Conclusion

We show robust evidence that analysts affiliated with the owners of the followed firms are significantly more optimistic in their target prices and recommendations. They are also more likely to issue beatable earnings forecasts presumably to support the management of the followed firms with positive earnings surprises. Their recommendation upgrades a less informative than those of their peers and lead to 0.8% less price increases over a two-month period.

Our paper highlights the conflict of interest incurred when the analysts' employers own a stake in the followed firms. Such conflict of interests has been largely ignored by the literature and therefore our results add to this gap.

In this paper, we look at only the holdings of the analysts' employers. How analysts behave around the time their employers buy or sell the followed stocks may be an interesting direction for future research.

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Appendix: Names of 13F owners supposed to be Citigroup's subsidiaries

1	Afore Banamex S.A. de C.V.
2	Banco Citibank S.A.
3	Bank Handlowy W Warszawie S.A.
4	CBHK- Citibank London- 497 Kia Transition Asia Iad No.1
5	CBNY Citibank N.A. Private Bank
6	Citi Capital Advisors (UK)
7	Citi Investment Research (Hong Kong)
8	Citi Investment Research (US)
9	Citi Islamic Investment Bank E. C.
10	Citi Venture Capital International
11	Citi and Fubon Bank
12	Citi and Fubon Insurance
13	Citibank (Gersey)
14	Citibank (HK) S Life Insurance
15	Citibank (Hong Kong) PBGC
16	Citibank (Hong Kong) Sub Account Capital Securities Corp.
17	Citibank (London) Fund 112
18	Citibank (London) Jasdec General Deposit
19	Citibank (London) Legal General Stock Lending
20	Citibank (London) PGGM Intern Bare Japan
21	Citibank (London) Refund 115
22	Citibank (London) UK Resident
23	Citibank (Paris) San Paolo
24	Citibank (Switzerland) AG
25	Citibank Berhad & Associates
26	Citibank Canada
27	Citibank Channel Islands Limited
28	Citibank DTVM S.A.
29	Citibank Europe PLC LUX Banque Degroof LUX Non AIF Omnibus
30	Citibank Hong Kong SA Fund 115
31	Citibank International
32	Citibank International Financial Ltd
33	Citibank International PLC LUX Banque Degroof LUX-Non AIF Om
34	Citibank Korea Inc.
35	Citibank LON-JAS General Depot
36	Citibank London (Pension Fund Metal Technique Re BAD1B3)
37	Citibank London Pension Fund Metal Technique BAD1B4
38	Citibank London Pension Fund Metal Techniques Re BHD2A
39	Citibank London SA (Stitching Shell Pension Fund)
40	Citibank Ltd.
41	Citibank N.A.

42 Citibank N.A. (Hong Kong)
43 Citibank N.A. (London)
44 Citibank NA
45 Citibank NA New York S/A Intel Corporation
46 Citibank Overseas Investment Corporation
47 Citibank Rt.
48 Citibank Singapore
49 Citibank Taiwan Law and General Insurance (Retirement Manage
50 Citicorp Asia Pacific
51 Citicorp Bank (Switzerland)
52 Citicorp Capital Asia
53 Citicorp Equity Capital Ltd
54 Citicorp Global markets Inc.
55 Citicorp International Finance Corporation
56 Citicorp Inversora S.A.
57 Citicorp Investments Limited
58 Citicorp Investments Pty. Ltd.
59 Citicorp Small Cap Japanese Equity
60 Citicorp Trade Services Ltd
61 Citicorp Trust South Dakota
62 Citicorp Vendor Finance Europe Ltd.
63 Citigroup Alternative Investments LLC
64 Citigroup Asset Management (Singapore)
65 Citigroup Capital Partners II Employee Master Fund, L.P.
66 Citigroup Capital Partners Japan Ltd.
67 Citigroup Capital Ventures UK Limited
68 Citigroup Financial Products LLC
69 Citigroup First Investment Management Limited
70 Citigroup Global Market Limited
71 Citigroup Global Markets Financial Products LLC
72 Citigroup Global Markets Inc.
73 Citigroup Global Markets Incorporated (091)
74 Citigroup Global Markets Incorporated (120)
75 Citigroup Global Markets Incorporated (267)
76 Citigroup Global Markets Japan Inc.
77 Citigroup Global Markets Limited
78 Citigroup Global Markets Ltd.
79 Citigroup Global Markets Ltd. (IPB Fund 1)
80 Citigroup Global Markets Ltd. (IPB Fund 2)
81 Citigroup Global Markets Mauritius Pvt. Ltd.
82 Citigroup Inc
83 Citigroup International LLC
84 Citigroup Investments Inc.
85 Citigroup Japan Holdings Corporation
86 Citigroup Pension Plan
87 Citigroup Principal Investments Japan Company Ltd.
88 Citigroup Venture Capital International Brazil (Delaware), L

89 Citigroup Venture Capital International Growth Partnership,
90 Cititrust Colombia S.A.
91 Cititrust and Banking Corporation
92 Fideicomiso Banamex 11776-3
93 Fideicomiso Banamex 11783-6
94 Fideicomiso Banamex 13037-9
95 Fideicomiso Banamex 13799-3
96 Fideicomiso Banamex 13804-3
97 Fideicomiso Banamex 14107-9
98 Fideicomiso Banamex 14473-6
99 Fideicomiso Banamex 14496-5
100 Fideicomiso Banamex 14497-3
101 Fideicomiso Banamex 144981
102 Fideicomiso Banamex 16436-2
103 Fideicomiso Cititrust IFC Suramericana
104 Fideicomiso Cititrust Suramericana II
105 Impulsora de Fondos Banamex, S.A. de C.V., Sociedad Operador
106 Koram Bank
107 Nikko Citi Trust and Banking Corporation
108 Salomon Smith Barney
109 The Travelers Companies, Inc.

4 Director compensation, stock price crash risk and analyst coverage

Abstract: We show that excessive compensation of outside directors is associated with bad-news hoarding and stock price crash risk. This relationship is largely attributed to excessive stock-based compensation but not cash compensation. We also demonstrate that excessive compensation is associated with higher information asymmetry, as evidenced by less accurate analyst forecasts of stock price. These findings cast doubts on the effectiveness of stock-based compensation in aligning the incentives of directors with shareholders' interest but are consistent with prior studies which document the adverse effects of stock-based compensation on corporate governance.

Keywords: director compensation, stock price crash, stock-based compensation

JEL codes : G14, G24, G34, M12

4.1 Introduction

Remuneration policy is one of the key elements of corporate governance. It provides appropriate incentives for the agent, i.e. executives and other employees, to work in the best benefit of the principal, i.e. shareholders (Jensen and Meckling, 1976). There is a large body of research analyzing executive remuneration policy and its effects on corporate performance (Matolcsy and Wright, 2011) and corporate risk (Gormley et al., 2013). However, the literature on outside director compensation is much less developed. Studying director compensation is important, because the board of directors is the key player in corporate governance. Outside directors, just like the executives, are expected to act in the interest of the shareholders. As economic agents, appropriate remuneration design is needed to incentivize them to carry out this mission.

One simple, intuitive question to ask is whether outside directors should be paid more to be motivated to monitor executives rather than to collude with them. Fama and Jensen (1983) posit that the answer is no, because outside directors are most effective when their compensation is "small". Brick et al. (2006) corroborate this view by demonstrating that excessive director compensation is associated with excessive CEO compensation. Moreover, they point out that excess director compensation has a negative effect on risk-adjusted stock returns. They attribute this phenomenon to "mutual back scratching" or "cronyism". They argue that overpaid directors may be concerned with protecting their income and avoid making a row with the executives. The overpaid directors thus refrain from raising criticism and fail to perform their monitoring duty effectively to the detriment of shareholders' interest.

This paper aims at extending the analysis of Brick et al. (2006). While they looked at the relationship between excess compensation of directors and stock returns, we investigate the effect of excess director compensation on stock price crash risk. Specifically, we use extreme

left-tailed observations of weekly stock returns to represent stock price crashes and find that excess compensation of directors is related to significantly higher risk of price crashes. In addition, we examine the relationship between director excess compensation and a specific type of price crash, that is crashes when bad-news hoarding is revealed. We find that excess director compensation significantly increases the likelihood of crashes caused by bad news hoarding. This is consistent with the view that excess compensation renders directors ineffective in their monitoring role.

Van den Berghe and Levrau (2004) point out that while directors' compensation is included in all corporate governance rating systems, there is little knowledge on what should be the appropriate, best practice. Stock-based compensation is especially controversial. Prior studies find that CEOs' stock-based compensation generates conflicts of interest and has negative effects on CEOs' behavior and firm risk (Benmelech et al., 2010). Consistently, we find that stock-based compensation significantly increases stock price crash risk. In contrast, cash compensation does not contribute at all to the effect of excess director compensation on stock price crash risk.

Additionally, we relate director excess compensation to asymmetric information surrounding the firm. As bad-news hoarding makes it harder for investors to evaluate firm prospect, analyst reports can be valuable for information discovery in these firms. Nevertheless, bad-news hoarding makes information asymmetry more severe, thus can make it harder for analysts to perform their job. By looking at the relationship between analyst coverage and price crashes due to bad news hoarding, we can see whether analyst reports are valuable when asymmetric information is high. We find that firms covered by more financial analysts are less likely to experience stock price crashes due to bad-news hoarding. Moreover, the time length of bad news hoarding until information is revealed is significantly shorter when the firms is covered by more analysts, suggesting that analyst coverage improves information discovery.

This result is consistent with prior literature which shows that analyst coverage reduces asymmetric information and deter firm's management from hiding information (Yu, 2008, Charitou et al., 2019, Ivković and Jegadeesh, 2004, Loh and Stulz, 2018).

In summary, we add to a large literature that examines the problems in corporate governance that hinder the board of directors from performing their tasks effectively. We answer Van den Berghe and Levrau (2004)'s concern about director stock-based compensation by pointing out that paying outside directors with stock is indeed not healthy for the board, the corporate governance system and the firm as a whole. Our findings also highlight the value of analyst coverage in the financial market.

The rest of the paper is structured as follows: Section 4.2 reviews the literature; Section 4.33 develop hypotheses, methodology and variable construction; Section 4.4 describes the data and presents selected results; Section 4.5 concludes.

4.2 Literature review and hypotheses

4.2.1 Director compensation

As the board of directors is the most important component of a firm's corporate governance system, it has been extensively researched. The prominent views are based on agency theory, stewardship theory, and resource dependence theory. Agency theory posits that executives are all selfish rational economic agents, whose interest conflicts with the interest of shareholders (Jensen and Meckling, 1976, Fama and Jensen, 1983). Consequently, in order to fulfil its obligations, the board must be unaffected by the executives' influence. Research based on agency theory emphasizes the composition and structure of the board. For example, empirical research has shown that board independence improves firm performance in many countries (Dahya et al., 2008, Black and Kim, 2012, Liu et al., 2015). In contrast, the stewardship theory posits that over-monitoring is unnecessary because executives are

trustworthy, know best about the company, and thus can make more informed decisions (Donaldson, 1990). This leads to the prediction that firm performance will be higher in firms where directors are less independent (Muth and Donaldson, 1998). Empirical evidence corroborates that independent directors may not work as intended (Fernandes, 2008). Under the resource dependence theory, the board of directors is considered to be an important link between the firm and external resources (Hillman et al., 2000, Pfeffer, 1973, Hillman et al., 2009), whereas the definition of resources is contextual. Empirical work stretching over several decades has not consistently confirmed or refuted any of these views, but indicates that each of these views can explain particular features of the governance system (Nicholson and Kiel, 2007).

CEOs, according to agency theory, will find it in their interest to circumvent board monitoring to maximize their utility, notably his compensation. While boards are expected to design the compensation structure that can motivate CEOs to work in shareholders' interest (Bebchuk and Fried, 2003, Laux and Laux, 2009), boards themselves must be equipped with the capacity to fulfil their responsibility. Boyd (1994) finds that CEO compensation is higher in firms with weak board control. Chhaochharia and Grinstein (2009) find that increase in board independence reduces CEO compensation.

Capacity and independence, however, may not be enough for boards to be committed to their job, but appropriate economic incentives driving their diligence are also important (Cordeiro et al., 2000). Although directors are expected to act in the interest of shareholders they have "few direct incentives to tie them to shareholders" (Harford, 2003). Director incentives may come from cash compensation, stock-based compensation, the possibility to gain new board seats, and after-market reputation if the firm performs well (Yermack, 2004). Some studies explore the design of incentive-based compensation that aligns the directors' interest with that of shareholders, especially when the need for monitoring is high (Fich and

Shivdasani, 2005, Linn and Park, 2005, Farrell et al., 2008). A number of studies have attempted to understand director incentives in different contexts such as in a takeover bid (Harford, 2003), when the CEO is more powerful (Ryan and Wiggins, 2004), or when directors are covered by liability insurance (Yuan et al., 2016).

More closely related to the results of our paper, Brick et al. (2006) demonstrate that excess compensation of directors is associated with higher CEO compensation and poorer stock performance. They argue that director excess compensation is a sign of cronyism, where directors avoid criticizing executives or "shake the boat" because they are obsessed with protecting their income.

4.2.2 Corporate governance, board of directors and stock price crash risk

A stock price crash is a deep decline in the stock price, likely due to bad news, and often related to the hoarding of bad news that is finally released. Stock price crash risk has been found to be associated with corporate governance characteristics. Generally speaking, better corporate governance tends to reduce stock price crash risk. For example, An and Zhang (2013) posit that dedicated long-term institutional block-holders have strong incentives to monitor and thus mitigate bad-news hoardings, leading to lower risk of stock price crashes. This is in agreement with other studies such as Callen and Fang (2013). They also observe that stock price crash risk increases with ownership by transient institutional investors who tend to trade rather than monitor. Andreou et al. (2016a) add that ownership structure but also accounting practices, board characteristics and managerial incentives attributes play an important role in predicting stock price crashes. Andreou et al. (2016b) demonstrate that firms with younger CEOs are more likely to experience stock price crashes. Kim et al. (2016) show that overconfident CEOs are related to higher price crash risk, especially in firms where they are more powerful.

Talking about corporate governance, one cannot afford to ignore board characteristics. Prior studies consistently point out that better board practices and board control can reduce bad-news hoarding and thus mitigate stock price crash risk. Andreou et al. (2016a) find that board size and the presence of corporate governance policy in a firm's mandate reduce crash risk. Chauhan et al. (2015) argue that bank-nominee directors, who have the ability and motivation to monitor, mitigate the conflicts of interest of block-holders and crash risk. In China, Li and Chan (2016) find that having a communist party member on the board significantly reduces crash risk. Yuan et al. (2016) find that directors' and officers' insurance covering them against legal liability arising from professional conduct improves corporate governance and significantly reduces price crash risk.

One important aspect of the board that is potentially a determinant of stock price crash risk, but has not been thoroughly examined, is director compensation. In a related study, Andreou et al. (2016a) find that crash risk increases with stock ownership of outside directors. This is in stark contrast with a number of studies arguing that stock-ownership aligns directors' interest with that of shareholders (Ryan and Wiggins, 2004, Fich and Shivdasani, 2005, Linn and Park, 2005). Indeed, it is not clear why stock-based compensation, which has been found to make executives behave badly both theoretically (Benmelech et al., 2010) and empirically (Kim et al., 2011a), does not create the same problems with directors as it does with executives.

4.2.3 Analyst coverage and information discovery

A natural question to ask is what remedy is available to assist information discovery and reduce the risk of bad-news hoarding. There come the stock analysts who regularly publish reports in which firms are analyzed in much details. Analysts can merely analyze and interpret the information provided by the firms, but also can provide new information content through their research (Ivković and Jegadeesh, 2004). Ayers and Freeman (2003) find that prices of

firms with analyst coverage incorporate future earnings earlier. Loh and Stulz (2018) show that analyst reports have higher impact in bad times when uncertainty is high. Charitou et al. (2019) show that when a valuable disclosure requirement is eliminated, analyst reports become more informational and compensate for the loss of publicly available information. Analysts have in-depth industry expertise and knowledge, often have interactions with firm management, and it is their job to follow firms closely. Accordingly, bad-news hoarding is less practical or can be revealed earlier if the firm is closely followed by dedicated analysts.

Analyst coverage does not only make bad-news hoarding less practical and be revealed earlier but can possibly deter firm management from bad-news hoarding to begin with. Analysts, like auditors and others, are after all agents of residual claims (shareholders and debtholders), and thus should act as an extra layer of external monitors to the firms' managers. Dyck et al. (2010) show that analysts are revealers in 24 over 142 cases of corporate fraud where the revealers belong to external governance. They argue that analysts have the incentives to reveal firms' fraud in order to improve their reputation and promotion. Consistently, Yu (2008) finds that firms followed by more analysts do less earnings management. Managers may therefore refrain from bad-news hoarding to avoid being exposed by analysts later on.

4.3 Data and variable construction

We acquire the data on compensation and CEO characteristics from ExecuComp database. Director compensation data is available in an unchanged format only after 2005. Before 2005, director compensation data is available in a different format. To maintain consistency, we do not use these data in our tests and only include the years from 2006 to 2018. Firm characteristics are obtained from Compustat. Stock returns are extracted from CRSP. Analyst forecasts are acquired from I/B/E/S. Table 1 summarizes key variables used in this paper.

4.3.1 Price crash

As we aim at testing the effect of excess director compensation on price crash risk, we need first to calculate price crash risk. We use the procedure that has been widely used in prior studies (Kim et al., 2011a, Hutton et al., 2009, Kim et al., 2011b). First, we calculate the residuals from the following expanded index model regression. Leads and lags of market returns are added following Dimson (1979) to allow for nonsynchronous trading.

$$r_{it} = \alpha + \beta_1 r_{m(t-2)} + \beta_2 r_{m(t-1)} + \beta_3 r_{mt} + \beta_4 r_{m(t+1)} + \beta_5 r_{m(t+2)} + \varepsilon_{it} \quad (1)$$

where r_{it} is the return of stock j in week t; r_{mt} is the return of the value-weighted market index d in week t. Weekly returns are calculated as cumulative daily returns of all trading days from Monday to Sunday. Regression (1) is fitted across all firms in the period spanning from week T-53 to week T where T is the end of the fiscal year of each firm i.

Then, we define firm-specific weekly return (*FSWR*) as the natural log of one plus the residual from regression (1)

$$FSWR_{it} = \ln(1 + \varepsilon_{it}) \quad (2)$$

In previous studies, crashes are defined as *FSWR* falling 3.09 (Hutton et al., 2009) (Hutton et al. 2009) to 3.2 (Kim et al. 2016) standard errors below the mean. We choose 3.2 to assure that the frequency of crashes is less than 0.1% in the normal distribution. A crash week of a firm is then defined as when *FiSWR* is 3.2 times of standard deviation below its mean. We define *DCRASH* as a dummy taking the value of one if the firm experience at least one crash week during a fiscal year and zero otherwise. *DCRASH* will be used as the dependent variable in our models.

4.3.2 Excess director compensation

We estimate a director compensation regression based on firm characteristics and CEO characteristics following Brick et al. (2006). Firm characteristics such as size,

profitability, risks, stock return are important in explaining director compensation. Moreover, the level of monitoring may be dependent on CEO characteristics such as expertise and experience. Thus, we use CEO characteristics as control variables in the director compensation regression. We also have year dummies and industry dummies as in Brick et al. (2006).

Unlike Brick et al. (2006) we do not use R&D expenses, advertising expenses and CEO gender and number of board meetings as control variables. As there are many missing observations for R&D expenses and advertising expenses, including these variables would significantly reduce the number firms for which we can estimate excess compensation. In addition, we were unfortunately not able to collect the data on CEO gender and number of board meetings. Probably due to similar difficulties, many previous studies model director compensation without these variables (Ryan and Wiggins, 2004, Chen et al., 2019).

We estimate the equation:

$$\text{DIR\_COM}_{it} = \alpha + \beta_m \sum(Firm\ controls + CEO\ controls) + \vartheta_{it} \quad (3)$$

where DIR_COM is natural logarithm of director total compensation as reported in SEC filling.

The residuals from regression (3) are the part of director compensation that are not explained by the need of monitoring as characterized by firm controls and CEO controls. These residuals are defined as director excess compensation (*EXDIRCOM*), which is the main independent variable of interest.

4.3.3 Control variables

In order to model price crash risk, we control for firm characteristics and CEO characteristics. Details of these variables can be found in Table 1. Following Andreou et al. (2016a), we also control for years and industries.

Additionally, we draw from recent studies the variables that have been reported to affect price crash risk, including CEO stock-based compensation, CEO over-confidence, and accrual earnings. Benmelech et al. (2010) demonstrate that stock-based compensation is associated with bad-news hoarding, overvaluation and subsequent stock price crashes. Kim et al. (2016) find that stock price crash risk is significantly higher in the firms with over-confident CEOs. Kim and Zhang (2016) show that conservative accounting policies is related with lower stock price crash risk. Zhu (2016) shows that higher accruals predict higher price crash risk. We control for these factors in our models.

We measure CEO overconfidence based on their stock-options following prior studies (Malmendier and Tate, 2005, Campbell et al., 2011, Kim et al., 2016). Malmendier and Tate (2005) define CEOs as overconfident if the CEOs do not exercise stock options that are more than 67% in the money. We adopt this 67% moneyness cutoff to identify overconfident CEOs using the following calculation. First, we estimate average per option value as total value of unexcised in-the-money exercisable options divided by the number of exercisable options. Then, we estimate the exercise price by subtracting the average per option value from stock price at the end of the fiscal year. We calculate the average percent moneyness of the options as the average per option value divided by exercise price. We create the dummy variable *CONFI* that takes the value of one if percent moneyness is higher than 67% and zero otherwise. *CONFI* identifies overconfident CEOs because they should have exercised the options that deeply in the money instead of holding them.

We measure discretionary accruals using a modified Jones model that is widely used in prior studies (Kothari et al., 2005, Dechow and Sloan, 1995, Jones, 1991). The following cross-sectional regression is fitted each year using all firms in the same Fama-French 48-industry classification.

$$TACC_{it} = \alpha_{it} + \beta_1 \frac{1}{ATA_{it}} + \beta_1 \frac{\Delta SALE_{it}}{ATA_{it}} + \beta_3 \frac{PPE_{it}}{ATA_{it}} + \varepsilon_{it} \quad (4)$$

where *TACC* is total accruals, defined as the change in non-cash working capital and non-current operating assets. *ATA* is average total assets between the beginning and the end of fiscal year; *ΔSALE* is change in sales; *PPE* is net property, plant and equipment.

The residuals from regression (4) is discretionary accruals (*DIS_TACC*).

4.3.4 Descriptive statistics

Table 1 summarizes statistics and definitions of key variables. Overall, 22.2% firm-years experienced stock price crash during our sampled period. This is a bit higher than other studies for the U.S market such as Andreou et al. (2016b) and Kim et al. (2016), who show that the number is 19.2% and 17.2%, respectively. The difference may be due to sample selection and data trimming. Because the measure of crashes is based on an extended index model, market movement has been extensively accounted for. Therefore, the distribution of crashes is not concentrated only in periods of market stress. It is true, however, that there are more crashes in 2008 than in all other years of our sampled period.

On average, the cash component in total compensation is 26.2%, suggesting that CEOs are predominantly paid by stock-based compensation. This number is comparable to that observed in previous studies (Brick et al., 2006, Dai et al., 2020).

Mean FOLLOW shows that, on average, each firm is followed by 13.76 analysts, but the number varies hugely, as indicated by a standard deviation of 9.8.

We employ a number of firm-specific variables controlling for profitability, leverage, risk, investment, market valuation and historical stock returns. We also control for CEO characteristics including their age, experience, stock ownership, whether they join the company

before becoming CEOs, and whether they simultaneously serve as chairman of the board. Details of these variables can be found in Table 1.

Table 2, column 1 presents the director compensation regression, whose residuals are used as the measure of excess director compensation (EXDIRCOM). This variable is then used as an explanatory variable in the CEO compensation regression in column (4). Director excess compensation has a strongly significant, positive relationship with CEO compensation. This is in accordance with Brick et al. (2006)'s results on cronyism. Boards are expected to design compensation schemes that provide the executives with appropriate incentives (Bebchuk and Fried, 2003), CEO compensation is higher in firms where board control is weaker or board members are less independent (Boyd, 1994, Chhaochharia and Grinstein, 2009).

Note that *EXDIRCOM* is estimated for each director. In order to test the relationship between price crash risk and excess director compensation, however, we need a variable that represents excess director compensation on firm level. For this, we simply use the mean of EXDIRCOM for each firm in each year.

Table 1: Summary statics and definitions of key variables

Variable	Obs.	Mean	S.D.	Variable definition
DCRASH	20,736	0.222	0.416	Stock price crash. equals one if the firm experiences at least one crash week during the fiscal year and zero otherwise. See Section 4 for more detail.
DIREXCOM	17,139	0.010	0.419	Director excess compensation. See Section 4 for more detail.
CEOCASH	18,815	0.262	0.216	Fraction of cash compensation as a proportion of over the CEO's total compensation.
CEOCOM	18,829	8.283	1.221	Natural logarithm of the CEO's total compensation as reported in SEC filings.
DISTACC	21,531	-0.026	0.165	Discretionary accruals, as the residuals from regression (4). See Section 4 for more detail.
CONFI	26,242	0.480	0.5	Equals one if the CEO is overconfident and zero otherwise. See Section 4 for more detail.
FOLLOW	19,183	13.76	9.824	The number of financial analysts covering the firm.
ROA	25,797	0.041	0.115	Return on assets. Calculated as EBIT divided by total assets.
MROA	22,606	0.089	0.098	Average ROA over the last three years.
SROA	22,602	0.021	0.029	Cash flow risk. Calculated as the standard deviation of ROA over the last three years.
DEBT	26,136	0.237	0.218	Total debt over total assets (book values).
MV	23,881	7.573	1.667	Natural logarithm of market capitalization.
BM	23,799	0.486	0.527	Book-to-market ratio.
CAPEX	24,165	0.051	0.055	Capital expenditure.
PPE	25,735	0.550	0.432	Plant, property and equipment.
LNEMP	24,005	1.654	1.703	Natural logarithm of the number of employees.
LNSALE	24,197	7.360	1.649	Natural logarithm of sales.
RET	24,564	0.280	1.435	Excess stock returns. Calculated as holding-period return over the past three years less the market value-weighted return during the same period.
SDRET	24,460	0.117	0.067	Stock volatility, as standard deviation of monthly stock return over the past 36 months.
SHROWN	16,018	2.808	6.196	The percentage of total shares owned by CEO.
AGE	25,768	55.78	7.321	The CEO's age.
DUAL	26,221	0.477	0.500	equals one if the CEO is also the chairman of the board and zero otherwise.
INTERNAL	26,221	0.257	0.437	Equals one if the CEO joined the company before the year he/she became CEO.
EXPER	26,221	7.019	7.187	The number of years the CEO is the CEO of the firm.

Table 2: Compensation regressions

This table presents the results from compensation regressions using a pooled-OLS model. The residuals from the regression in column (1) proxy for director excess compensation. See Section 4 and Table 1 for variable definitions. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	$DIRCOM_t$		$CEOCOM_t$	
	(1)	(2)	(3)	(4)
ROA_{t-1}	-0.0451	-0.0301	-0.177***	-0.153***
	(-1.19)	(-0.80)	(-3.58)	(-3.12)
$MROA_{t-2,t}$	-0.146***	-0.108***	-0.441***	-0.506***
	(-3.61)	(-2.68)	(-8.34)	(-9.65)
$SROA_{t-2,t}$	0.348***	0.364***	-0.244***	-0.239**
	(4.81)	(5.05)	(-2.58)	(-2.55)
$DEBT_{t-1}$	0.0903***	0.0565***	0.424***	0.425***
	(9.72)	(6.09)	(34.94)	(35.34)
MV_{t-1}	0.162***	0.146***	0.203***	0.207***
	(72.17)	(64.05)	(69.02)	(71.09)
BM_{t-1}	-0.00263***	-0.00213***	-0.00625***	-0.00636***
	(-9.66)	(-7.83)	(-17.43)	(-18.00)
$CAPEX_{t-1}$	0.463***	0.487***	-0.389***	-0.344***
	(9.12)	(9.63)	(-5.85)	(-5.23)
PPE_{t-1}	-0.175***	-0.150***	-0.314***	-0.304***
	(-12.07)	(-10.38)	(-16.59)	(-16.21)
$LNEMP_{t-1}$	-0.0198***	-0.0229***	0.0411***	0.0386***
	(-7.71)	(-8.96)	(12.20)	(11.57)
$LNSALE_{t-1}$	0.0443***	0.0310***	0.166***	0.168***
	(13.58)	(9.48)	(38.75)	(39.62)
$RET_{t-2,t}$	0.00732***	0.00381**	0.0445***	0.0440***
	(4.88)	(2.55)	(22.56)	(22.66)
$SDRET_{t-2,t}$	0.675***	0.695***	-0.228***	-0.210***
	(16.11)	(16.64)	(-4.17)	(-3.86)
$SHROWN_t$	-0.00946***	-0.00694***	-0.0328***	-0.0318***
	(-24.88)	(-18.03)	(-66.04)	(-64.27)
AGE_t	-0.000686**	-0.000897***	0.00337***	0.00303***
	(-2.51)	(-3.30)	(9.45)	(8.58)
$DUAL_t$	-0.0330***	-0.0448***	0.151***	0.146***
	(-8.87)	(-12.08)	(31.03)	(30.42)
$INTERNAL_t$	0.0298***	0.0333***	-0.0365***	-0.0378***
	(7.48)	(8.39)	(-6.99)	(-7.32)
$EXPER_t$	-0.000294	-0.000564*	0.00229***	0.00330***
	(-0.98)	(-1.88)	(5.84)	(8.46)
CEO_COM_t		0.0798***		
		(40.74)		
DIR_EXCOM_t				0.135***
				(40.74)
Constant	3.514***	3.088***	5.361***	5.329***
	(149.89)	(120.79)	(174.61)	(175.45)

	$DIRCOM_t$		$CEOCOM_t$	
	(1)	(2)	(3)	(4)
Year dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
N	152,502	152,253	156,435	152,253
R-squared	0.245	0.253	0.447	0.463

Table 3 shows the evolution of CEO compensation, director compensation, and director excess compensation through time. CEO compensation is well-known to increase rapidly during the last decades (Frydman and Saks, 2010). Bebchuk and Fried (2009) posit that such increase is due to executives taking advantage of weak corporate governance. Table 3 shows that not only executive compensation, but also director compensation sharply increases through time. Brick et al. (2006) argue that excessive director pay makes them ineffective. Increasing director compensation may be one of the tactics of the executives to disable the board's ability to control executives' rent extraction. Table 3 also reveals that the cash component of CEO compensation is shrinking through time. In the following, we examine whether the proportion of cash and stock-based compensation in CEO total compensation has any effect on stock price crash risk and bad news hoarding.

Table 3: Compensation statistics by years

	CEOCOM		CEOCASH		DIRCOMMEAN		EXDIRCOM	
Year	Mean	Freq.	Mean	Freq.	Mean	Freq.	Mean	Freq.
2006	8.132	1,141	0.294	1,141	4.887	1,139	-0.003	985
2007	8.022	1,641	0.309	1,642	4.889	1,612	0.011	1,442
2008	8.007	1,610	0.320	1,610	4.917	1,583	0.017	1,437
2009	8.024	1,590	0.319	1,590	4.903	1,559	0.006	1,441
2010	8.201	1,565	0.275	1,565	5.009	1,537	0.003	1,424
2011	8.254	1,547	0.265	1,547	5.077	1,508	0.009	1,400
2012	8.270	1,515	0.266	1,515	5.104	1,491	0.003	1,368
2013	8.301	1,508	0.254	1,508	5.159	1,474	0.010	1,362
2014	8.441	1,483	0.231	1,483	5.237	1,455	0.006	1,361
2015	8.456	1,436	0.225	1,436	5.269	1,404	0.010	1,327
2016	8.509	1,380	0.214	1,380	5.300	1,362	0.021	1,297
2017	8.606	1,322	0.204	1,322	5.349	1,297	0.019	1,247
2018	8.656	1,091	0.201	1,091	5.383	1,082	0.016	1,048
All	8.283	18,829	0.262	18,830	5.104	18,504	0.010	17,139

4.4 Results

4.4.1 Excess director compensation, price crash risk, and bad-news hoarding

Table 4 relates stock price crash risk to excess compensation of directors. As the dependent variable is binomial, we fit the regressions using probit models. We control for firm characteristics, CEO characteristics, and some other factors that have been documented to affect stock price crash risk in prior studies. Dependent variables are in lagged form in order to reduce the effects of endogeneity (Brick et al., 2006).

The coefficients of *EXDIRCOM* shows that higher excess compensation of directors significantly increases the probability of stock price crashes. This relationship is robust in all model specifications. This is consistent with the view that director excess compensation is associated with cronyism, which renders their monitoring task ineffective (Brick et al., 2006). This result has important practical implications. Specifically, higher economic benefits may not motivate directors to act in the best interest of shareholders as intended.

Besides, Table 4 indicates that higher cash component of CEO compensation reduces the risk of stock price crashes. This is in line with prior literature which associates CEO stock-based incentives with higher conflicts of interest and bad-news hoarding (Benmelech et al., 2010), and also higher stock price crash risk (Andreou et al., 2016a). Additionally, higher discretionary accruals increases price crash risk, which is consistent with prior studies showing that accounting conservatism mitigates price crash risk (Kim and Zhang, 2016, Andreou et al., 2016a). Finally, in agreement with prior research (Kim et al., 2016), CEO overconfidence is associated with higher crash risk.

Table 4: Director excess compensation and price crash risk

This table presents the regressions on the relationship between director excess compensation (EXDIRCOM) and stock price crash (DCRASH) using probit models. See Section 3 and Table 1 for variable definitions. z-statistics in parentheses. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	Probit with random effects		Probit with year dummies and industry dummies	
	(1)	(2)	(3)	(4)
VARIABLES	$DCRASH_t$	$DCRASH_t$	$DCRASH_t$	$DCRASH_t$
$EXDIRCOM_{t-1}$	0.0631**	0.0901***	0.0612**	0.0889***
	(2.040)	(2.766)	(2.005)	(2.768)
$CEOCASH_{t-1}$	-0.281***	-0.290***	-0.219***	-0.221**
	(-3.396)	(-3.132)	(-2.631)	(-2.410)
$CEOCOM_{t-1}$	-0.0352***	-0.0320*	-0.0268*	-0.0258
	(-2.601)	(-1.894)	(-1.916)	(-1.377)
$DISTACC_{t-1}$	0.560***	0.392***	0.297***	0.268***
	(7.484)	(4.160)	(3.486)	(2.703)
$CONFI_{t-1}$	0.0892***	0.0748***	0.0491*	0.0362
	(3.403)	(2.577)	(1.816)	(1.214)
ROA_{t-1}		-0.711***		-0.573***
		(-3.965)		(-3.225)
$MROA_{t-1}$		1.024***		1.012***
		(5.587)		(5.483)
$SROA_{t-1}$		-1.424**		-1.509**
		(-2.178)		(-2.375)
$DEBT_{t-1}$		-0.218***		-0.182*
		(-2.585)		(-1.937)
MV_{t-1}		0.0216		0.0486**
		(1.080)		(2.243)
BM_{t-1}		-0.181***		-0.135***
		(-4.677)		(-3.895)
$CAPEX_{t-1}$		0.546*		0.675*
		(1.647)		(1.891)
PPE_{t-1}		-0.192***		-0.0585
		(-3.713)		(-1.041)
$LNEMP_{t-1}$		0.00786		-0.0144
		(0.446)		(-0.664)
$LNSALE_{t-1}$		-0.0172		-0.0150
		(-0.615)		(-0.491)
RET_{t-1}		-0.175***		-0.168***
		(-6.572)		(-6.436)
$SDRET_{t-1}$		1.064***		2.027***
		(3.329)		(5.646)
$SHROWN_{t-1}$		-0.00242		-0.00355
		(-0.888)		(-1.290)
AGE_{t-1}		-0.000562		-0.00108

	Probit with random effects		Probit with year dummies and industry dummies	
	(1)	(2)	(3)	(4)
VARIABLES	$DCRASH_t$	$DCRASH_t$	$DCRASH_t$	$DCRASH_t$
		(-0.260)		(-0.501)
$DUAL_{t-1}$		-0.0549*		-0.0171
		(-1.795)		(-0.551)
$INTERNAL_{t-1}$		-0.0678*		-0.0545
		(-1.933)		(-1.583)
$EXPER_{t-1}$		0.00376		0.00337
		(1.623)		(1.458)
Constant	-0.418***	-0.347*	-0.937***	-1.323***
	(-3.277)	(-1.658)	(-4.093)	(-3.908)
Clustered SE	Firm	Firm	Firm	Firm
N. Obs.	12,809	11,059	12,803	11,053

4.4.2 Director cash compensation versus stock-based compensation

Stock-based incentives are considered by agency theorists to be an effective way to align the executives' interests with those of shareholders (Jensen and Murphy, 1990). As such, the proportion of stock-based compensation in total compensation has surged during the past decades (Frydman and Jenter, 2010). However, stock-based incentives, especially stock options, contain fundamental shortcomings, one of which is that the executives do not share the downside risk with the shareholders (O'Connor et al., 2006). As they can enjoy the upside return without suffering downside risk, their behavior may unexpectedly become aggressive. Gande and Kalpathy (2017) find that CEO stock-based incentives are positively related to risk-taking in financial firms which then leads to insolvency. Bergstresser and Philippon (2006) find that aggressive earnings management is more pronounced when CEO compensation is tied to stock price. Benmelech et al. (2010) demonstrate that stock-based compensation induces executives to pursue sub-optimal investments and hide bad news. Risk taking, aggressive earnings management, and bad-news hoarding predict higher price crash risk.

Director stock-based compensation is also expected to better align directors' interests with those of shareholders (Fich and Shivdasani, 2005, Ryan and Wiggins, 2004) but also possibly suffer from the same shortcoming. As directors are more concerned with the stock price, they may be more tolerant towards aggressive behavior by the CEO destined to prop up the stock price, thus rendering their monitoring function compromised (O'Connor et al., 2006). Empirically, director stock-based incentives are found to be positively associated with higher likelihood of stock price crash (Andreou et al., 2016a, Kim et al., 2011a).

In Table 5, we investigate whether the undesirable effects of excess director compensation are due to excess cash compensation or excess stock-based compensation. First, we calculate director excess cash compensation (*EXDIRCASH*) and director excess stock compensation (*EXDIRSTOCK*) using the same procedure used to calculate director excess total compensation. We replace the dependent variable *DIRCOM* in Table 2, regression (1) by director cash compensation and director stock-based compensation. *EXDIRCASH* and *EXDIRSTOCK* are means of the residuals for each firm. We rerun the regressions in Table 4, replacing the independent variable *EXDIRCOM* by *EXDIRCASH* and *EXDIRSTOCK*. We omit the coefficients of firm controls and CEO controls to save space.

Column (1) and (3) indicate that excess cash compensation of directors does not have statistically significant effects on the probability of stock price crashes, despite having positive regression coefficients. On the contrary, column (2) and (4) show significant positive coefficients of excess director stock-based compensation, suggesting that stock price crash risk increases with excess director stock-based compensation. This is in line with the argument that stock-based compensation may compromise directors' monitoring function (O'Connor et al., 2006) and confirm the empirical evidence that director stock-based incentives worsen crash risk (Andreou et al., 2016a, Kim et al., 2011a).

Table 5: Director cash compensation, stock-based compensation and crash risk

This table presents the regressions on the relationship between director excess cash compensation (*EXDIRCASH*) and director excess stock-based compensation (*EXDIRSTOCK*) with stock price crash (*DCRASH*) using probit models. See Section 3 and Table 1 for variable definitions. z-statistics in parentheses. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	Probit with random effects		Probit with year dummies and industry dummies	
	(1) $DCRASH_t$	(2) $DCRASH_t$	(3) $DCRASH_t$	(4) $DCRASH_t$
$EXDIRCASH_{t-1}$	0.0172		0.0134	
	(0.534)		(0.424)	
$EXDIRSTOCK_{t-1}$		0.0572**		0.0596***
		(2.504)		(2.596)
$CEOCASH_{t-1}$	-0.314***	-0.304***	-0.247***	-0.241**
	(-3.399)	(-3.138)	(-2.719)	(-2.522)
$CEOCOM_{t-1}$	-0.0301*	-0.0303*	-0.0237	-0.0256
	(-1.886)	(-1.795)	(-1.353)	(-1.367)
$DISTACC_{t-1}$	0.373***	0.383***	0.252**	0.252**
	(3.950)	(4.022)	(2.534)	(2.514)
$CONFI_{t-1}$	0.0812***	0.0723**	0.0422	0.0311
	(2.796)	(2.460)	(1.416)	(1.034)
Constant	-0.361*	-0.360*	-1.294***	-1.387***
	(-1.747)	(-1.704)	(-3.947)	(-4.129)
Firm controls	Yes	Yes	Yes	Yes
CEO controls	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm
N. Obs.	10,979	10,838	10,973	10,832

4.4.3 Bad-news hoarding

While *DCRASH* is a measure of stock price crashes, it does not specify whether the crash is a result of new unexpected bad news, or a result of old-bad-news hoarding being revealed. Andreou et al. (2016b) argue that a break in a string of earnings increases accompanied by a stock price crash is an indication of bad news hoarding. We follow their approach and use three dummies to proxy for price crashes associated with bad-news hoarding. First, *BRCRASH1* equals one if the firm's stock price crashes in the current year, and earnings are negative in the current year and positive in the previous year, and zero otherwise. Second,

BRCRASH2 equals one if the firm's stock price crashes in the current year, and earnings are negative in the current year and positive in the previous two years, and zero otherwise. Third, *BRCRASH3* equals one if the firm's stock price crashes in the current year, and earnings are negative in the current year and positive in the previous three years, and zero otherwise. As the length of positive earnings before the break-crash event may be related to the extent of bad-news hoarding, we add a control variable *LENSTRG*, which is the number of consecutive positive earnings years before the break-crash event under the same CEO tenure.

Table 6 shows that director excess compensation is significantly and positively related to stock price crashes that are likely caused by bad-news hoarding. The magnitude of the coefficients of *EXDIRCOM* are much larger than those in Table 4.

Discretionary accruals, which indicate earnings management, are also positively related to price crash risk due to bad-news hoarding. Earnings management is the manipulation of reported earnings by the executives for personal purposes. High discretionary accruals are associated with stock return underperformance in later years (Xie, 2001). The longer the string of past consecutive positive earnings years (*LEN_STRG*), the higher the likelihood of price crashes related to bad-news hoarding.

4.4.4 Bad-news hoarding and analyst coverage

Analyst coverage may arguably have two conflicting effects on bad news hoarding. First, analyst attention can create more pressure on the management and make them more aggressive in hiding bad news. Second, financial analysts acting as agents of investors is a group of external monitors who have the duty as well as incentives to detect and reveal the management misrepresentation of stock prices. We shed new empirical light on these arguments by looking at the effects of analyst coverage on price crash risk associated with bad-news hoarding.

Table 6: Director excess compensation and bad news hoarding

This table presents the regressions on the relationship between director excess compensation (EXDIRCOM) and stock price crash associated with bad-news hoarding (BRCRASH1, BRCRASH2, BRCRASH3) using probit models. See Section 3 and Table 1 for variable definitions. z-statistics in parentheses. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	Probit with random effects			Probit with year dummies and industry dummies		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	$BRCRASH1_t$	$BRCRASH2_t$	$BRCRASH3_t$	$BRCRASH1_t$	$BRCRASH2_t$	$BRCRASH3_t$
$EXDIRCOM_{t-1}$	0.330***	0.311***	0.341***	0.349***	0.320***	0.327***
	(4.140)	(3.433)	(3.316)	(4.217)	(3.596)	(3.419)
$CEOCASH_{t-1}$	-0.467**	-0.355	-0.373	-0.477**	-0.394*	-0.464*
	(-2.122)	(-1.541)	(-1.481)	(-2.227)	(-1.688)	(-1.842)
$CEOCOM_{t-1}$	-0.0468	-0.0256	-0.0353	-0.0536	-0.0342	-0.0404
	(-1.519)	(-0.778)	(-1.020)	(-1.544)	(-0.798)	(-0.908)
$DISTACC_{t-1}$	0.844***	1.056***	1.080***	0.859***	1.104***	1.108***
	(4.598)	(5.101)	(4.866)	(4.235)	(5.032)	(4.596)
$CONFI_{t-1}$	0.00514	0.0286	-0.0418	-0.0134	0.0345	-0.00416
	(0.0851)	(0.437)	(-0.599)	(-0.200)	(0.474)	(-0.0530)
$LENSTRG_{t-1}$	0.0250**	0.0426***	0.0603***	0.0294***	0.0509***	0.0725***
	(2.515)	(3.464)	(4.562)	(3.454)	(5.384)	(6.912)
ROA_{t-1}	-3.803***	-3.915***	-3.751***	-3.642***	-3.751***	-3.585***
	(-10.28)	(-9.033)	(-8.601)	(-12.76)	(-12.06)	(-10.95)
$MROA_{t-1}$	1.966***	2.426***	2.528***	2.038***	2.349***	2.320***
	(5.003)	(5.902)	(5.765)	(4.590)	(4.730)	(4.311)
$SROA_{t-1}$	-4.874***	-6.911***	-7.645***	-4.735***	-7.076***	-7.555***
	(-3.390)	(-4.303)	(-4.000)	(-3.363)	(-3.890)	(-3.654)
$DEBT_{t-1}$	-0.147	-0.244	-0.226	-0.201	-0.269	-0.162
	(-1.016)	(-1.474)	(-1.257)	(-1.137)	(-1.385)	(-0.785)
MV_{t-1}	-0.134***	-0.170***	-0.218***	-0.138***	-0.173***	-0.211***
	(-3.365)	(-3.698)	(-4.106)	(-2.888)	(-3.203)	(-3.617)

	Probit with random effects			Probit with year dummies and industry dummies		
	(1)	(2)	(3)	(4)	(5)	(6)
BM_{t-1}	0.0277	0.0148	-0.00286	0.0517	0.0300	0.0271
	(0.558)	(0.262)	(-0.0453)	(0.734)	(0.376)	(0.315)
$CAPEX_{t-1}$	1.007	1.110	1.326	1.220	1.494	1.671
	(1.449)	(1.502)	(1.627)	(1.441)	(1.600)	(1.598)
PPE_{t-1}	-0.129	-0.0881	-0.155	-0.0922	-0.0321	-0.0444
	(-1.286)	(-0.804)	(-1.243)	(-0.773)	(-0.247)	(-0.305)
$LNEMP_{t-1}$	-0.0377	-0.0309	-0.0338	0.00443	0.00488	-0.00440
	(-1.146)	(-0.857)	(-0.882)	(0.0946)	(0.0957)	(-0.0804)
$LNSALE_{t-1}$	0.0899*	0.0815	0.107*	0.0603	0.0552	0.0736
	(1.894)	(1.552)	(1.848)	(0.954)	(0.788)	(0.974)
RET_{t-1}	-0.391***	-0.439***	-0.526***	-0.404***	-0.471***	-0.601***
	(-4.195)	(-4.490)	(-4.527)	(-6.482)	(-6.517)	(-7.065)
$SDRET_{t-1}$	0.201	0.0208	-0.113	1.063	0.636	0.0941
	(0.308)	(0.0309)	(-0.148)	(1.268)	(0.651)	(0.0858)
$SHROWN_{t-1}$	-0.00117	-0.00177	-0.000891	-0.00190	-0.00205	-0.00279
	(-0.228)	(-0.344)	(-0.166)	(-0.305)	(-0.311)	(-0.404)
AGE_{t-1}	0.00250	0.00365	0.00280	0.00272	0.00398	0.00436
	(0.576)	(0.766)	(0.526)	(0.574)	(0.788)	(0.800)
$DUAL_{t-1}$	-0.0792	-0.0183	-0.0111	-0.0888	-0.0260	-0.0204
	(-1.199)	(-0.259)	(-0.147)	(-1.258)	(-0.346)	(-0.253)
$INTERNAL_{t-1}$	-0.0836	-0.126	-0.103	-0.0542	-0.0983	-0.0659
	(-1.159)	(-1.574)	(-1.210)	(-0.676)	(-1.125)	(-0.716)
$EXPER_{t-1}$	-0.00555	-0.00510	-0.00165	-0.00640	-0.00614	-0.00340
	(-1.049)	(-0.893)	(-0.269)	(-1.161)	(-1.060)	(-0.558)
Constant	-1.402***	-1.570***	-1.450***	-1.805**	-1.583*	-1.532**
	(-3.142)	(-3.388)	(-2.905)	(-2.340)	(-1.955)	(-2.294)
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm
Observations	11,059	11,059	11,059	10,437	10,437	10,349

Table 7 fits all regressions in Table 6, adding the number of analysts covering the firm (*FOLLOW*) as an independent variable, together with its interaction with the length of positive earnings string. Unreported tests show that when the interaction term is not included, *FOLLOW* has a significant, negative effect on price crash risk associated with bad-news hoarding. However, when the interaction term is present, it captures all the effect and make the coefficients of *FOLLOW* insignificant. While *LENSTRG* shows that longer strings of positive earnings have higher risk of bad-news hoarding and subsequent stock price crashes, the negative coefficients of the interaction term show that *FOLLOW* has a mediating effect on this relationship: long positive earnings string in firms with higher analyst coverage is less likely to suffer price crashes due to bad-news hoarding in the future. This is probably due to either analyst coverage discourages firm management from bad-news hoarding in the first place, or analysts are able to reveal bad news earlier, resulting in shorter strings of consecutive bad positive earnings.

4.5 Conclusion

In this paper, we find that higher compensation may not necessarily motivate outside directors to work in shareholders' interest as intended. On the contrary, we offer evidence that outside directors may collude more with the CEO if they are overpaid. We also show that the adverse effects of excess compensation on directors' performance are most likely due to stock-based compensation and not cash compensation. That directors are unable to effectively monitor the executives expose the firm to higher likelihood of stock price crashes in general and due crashes to bad-news hoarding in particular. These results are consistent with prior studies which find that stock-based compensation worsen the agent-principal conflicts of interest.

We also find evidence that financial analyst coverage has a mediating effect on the relationship between excess director compensation and stock price crashes due to bad-news hoarding. This result confirms the useful role of financial analysts as agents of investors and outside monitors of firm management.

Table 7: Analyst coverage and bad news hoarding

This table presents the regressions on the relationship between analyst coverage (FOLLOW) and stock price crash associated with bad-news hoarding (BRCRASH1, BRCRASH2, BRCRASH3) using probit models. See Section 3 and Table 1 for variable definitions. z-statistics in parentheses. *, **, *** denote significance levels of 10%, 5%, 1% respectively.

	Probit with random effects			Probit with year dummies and industry dummies		
	(1)	(3)	(5)	(7)	(8)	(9)
VARIABLES	$BRCRASH1_t$	$BRCRASH2_t$	$BRCRASH3_t$	$BRCRASH1_t$	$BRCRASH2_t$	$BRCRASH3_t$
$EXDIRCOM_{t-1}$	0.308***	0.298***	0.331***	0.307***	0.288***	0.287***
	(3.585)	(3.089)	(2.954)	(3.550)	(3.062)	(2.740)
$FOLLOW_{t-1}$	0.000761	0.00556	0.0107	-0.000730	0.00302	0.0104
	(0.117)	(0.848)	(1.448)	(-0.109)	(0.433)	(1.315)
$LENSTRG_{t-1}$	0.0535***	0.0723***	0.0963***	0.0590***	0.0803***	0.108***
	(3.268)	(3.725)	(3.891)	(4.440)	(5.959)	(7.597)
$FOLLOW_{t-1}$ x $LENSTRG_{t-1}$	-0.00199***	-0.00226***	-0.00258***	-0.00217***	-0.00245***	-0.00282***
	(-2.949)	(-3.453)	(-3.667)	(-3.381)	(-4.071)	(-4.521)
$CEOCASH_{t-1}$	-0.573**	-0.447*	-0.471*	-0.577**	-0.482*	-0.568*
	(-2.293)	(-1.719)	(-1.667)	(-2.223)	(-1.784)	(-1.906)
$CEOCOM_{t-1}$	-0.0698**	-0.0401	-0.0441	-0.0693**	-0.0405	-0.0381
	(-2.120)	(-1.128)	(-1.063)	(-2.037)	(-1.107)	(-0.893)
$DISTACC_{t-1}$	0.526***	0.730***	0.660***	0.494**	0.759***	0.669***
	(2.613)	(3.277)	(2.728)	(2.393)	(3.468)	(2.747)
$CONFI_{t-1}$	0.0227	0.0400	-0.0336	-0.0201	0.0132	-0.0358
	(0.336)	(0.554)	(-0.438)	(-0.290)	(0.177)	(-0.444)
Constant	-1.832***	-2.083***	-2.016***	-2.401***	-2.334***	-2.278***
	(-3.548)	(-3.838)	(-3.385)	(-2.708)	(-2.584)	(-3.016)
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes

	Probit with random effects			Probit with year dummies and industry dummies		
	(1)	(3)	(5)	(7)	(8)	(9)
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Firm	Firm	Firm	Firm	Firm	Firm
Observations	9,092	9,092	9,092	8,453	8,358	8,283

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5 Conclusion

During the past two decades, the professional environment in which stock analysts interact with stakholders and manufacture their reports has been continuously changing. This poses new challenges and keep the topic of stock analyst behavior and their effects on the capital market interesting for academics, despite a dense body of literature.

In this thesis, we study research questions new to that literature. In the first paper, we show that the well-known optimism of equity underwriter-affiliated analysts is more likely to support the aftermarket of the underwritten security than to nurture the business relationship with the issuer as the prominent view in the literature posits. In the second paper, we highlight the conflicts of interest of stock analysts whose employers own the followed firms' stocks, by showing that they issue more optimistic and in effect less accurate forecasts. The third paper shows that excessive compensation of outside directors is associated with bad corporate governance and increases information asymmetry, and analyst coverage can mitigate this risk.

There are several potential ideas for future research based on these studies. For example, while we have looked at ownership of the analysts' employers, how they coordinate trading in the followed stocks with analyst forecasts is another interesting issue to be examined.