Bond Analysts' Forecasts on Cash Flows and Earnings*

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ABSTRACT

Using sell-side bond analysts' forecasts, collected from their debt reports for the period 2001-2010, this study examines the determinants and properties of bond analysts' forecasts on cash flows and earnings. Initial evidence indicates that the probability to issue cash flow (earnings) forecasts is greater (smaller) for bond analysts than for equity analysts, consistent with the notion that cash flow (earnings) information is more (less) important to bond investors than for stock investors. My analysis further shows that bond analysts are less optimistic in both cash flow and earnings forecasts than equity analysts, implying that bond analysts' view on firm's future performance is driven by bond investors' asymmetric demand for good news and bad news. In addition, bond analysts' cash flow (earnings) forecasts are more (less) accurate than equity analysts' cash flow (earnings) forecasts, which manifests bond investors' stronger demand for reliable information on future cash flows than for earnings. Finally, my additional cross-sectional analysis reveals that bond analysts are more likely to issue cash flow forecasts for firms with greater volatility of cash flows and under more severe liquidity constraint. Overall, this study enhances our understanding of the informational role bond analysts play in the bond market through their forecasting activities.

Keywords: Bond Analysts; Equity Analysts; Cash Flow Forecasts; Earnings Forecasts; Forecast Bias and Accuracy

JEL Classifications: D84; G17; G24; G29; M41

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1. Introduction

Since Amazon.com started to build up a dominant position in e-commerce, and enjoyed triple-digit growth rates and expansion into new product lines, the market had positive expectations about Amazon's future profitability and growth. After hitting a peak of stock price around $106 on Dec. 10, 1999, Amazon's stock price appeared to trade at the range between $45 and $55 until mid-June of 2000. Some investors were starting to question about the future profitability and growth. Nonetheless, there were still plenty of investors and equity analysts who had faith in Amazon (Hof, Sparks, Neuborne, and Zellner, 2000).

On June 22, 2000, one bond analyst, Ravi Suria, hired by Lehman Brothers Inc., released a scathing report about Amazon's deteriorating credit situation. He argued that excessive debt and poor inventory management would make Amazon's operating cash-flow situation worse the more it sells, consequently making it difficult for the company to meet its debt obligations by the end of the first quarter of 2001.[1] However, many equity analysts thought Suria was overly pessimistic and continued to focus on Amazon's potential earnings growth.[2] Eventually, Amazon realized a huge amount of negative cash flows, and the bond analyst saved Lehman's clients millions of dollars when he cautioned them about the crushing wave of debt about to envelop the telecom industry, giving them plenty of time to get out before the bubble burst. Investors who followed Suria's advice to put their money in the oil and energy sectors also got rich (Khan, 2001). As evident from this anecdotal evidence, bond analysts consider cash flow information more important than earnings information, while equity analysts put more weight on earnings information rather than cash flow information.

[1] In his bond report, Suria states "The fundamental problem lies in the fact that Amazon does not generate positive net cash flow per unit of product it sells."
[2] Henry Blodget, a Merrill Lynch & Co. (equity) analyst, said that "I'm not at all concerned about the cash side." According to a JP Morgan & Co. (equity) analyst, Tom Wyman: "Their (Amazon's) operating margin will be twice that of brick-and-mortar retailers."

This study investigates the determinants and properties of cash flow and earnings forecasts issued by sell-side bond analysts.[3,4] Specifically, I first raise two questions: Between bond analysts and equity analysts, which analysts are more likely to issue cash flow forecasts? What about earnings forecasts? Further, I compare the bias and accuracy of equity and bond analysts' forecasts. Finally, I ask why some bond analysts issue cash flow forecasts while others do not, and why some bond analysts are more likely to issue an earnings forecast together with a cash flow forecast. This study attempts to answer these questions.

The informational role of sell-side debt analysts is important for several reasons. First, both bond and stock markets are important to finance capital for firms. The amount of outstanding and newly issued debt is substantial compared to that of equity. For example, at the end of 2010, the amount of total U.S. outstanding debt was 343% of total GDP, while that of outstanding equity was 119% of total GDP.[5] Despite the significance of public debt markets, there has been relatively less research on the corporate bond market, particularly on the role of bond analysts in the bond market. Second, the recent credit market crises, in both debt/credit derivative and housing markets, accelerated the criticism of the failure of credit rating agencies [hereafter 'CRAs'] in providing relevant and reliable predictions on the credit risk of firms. Many investors and regulators have casted doubts about the quality of credit rating reports issued by CRAs. Although Cheng and Neamtiu (2009) find that CRAs have increased the information quality of their ratings following recent regulatory changes, such as the Sarbanes and Oxley Act (2002), bond investors and bond analysts argue that the credit information provided by the CRAs

[3] Throughout the paper, I use 'debt analysts', 'bond analysts', 'sell-side debt analysts', and 'sell-side bond analysts' interchangeably. Also, 'debt reports' or 'bond reports' refer to analyst reports issued by sell-side bond analysts.
[4] I focus on corporate bonds from debt research reports. Hence, governmental debt, macroeconomic or industry research, and research conducted by credit rating agencies are excluded.
[5] Roxburgh, Lund, and Piotrowski, 2011, available from (http://www.mckinsey.com/insights/global_capital_markets/mapping_global_capital_markets_2011).

is not timely and accurate, which limits the usefulness of the credit information.[6] Under such circumstances, research on debt analysts has been recently called for by academics (Berger, 2011; Beyer, Cohen, Lys, and Walther, 2010; Kolasinski, 2009; Mangen, 2013). Beyer et al. (2010) encourage researchers to investigate issues related to the development of debt markets and their interactions with equity markets when they examine the valuation role of accounting information. Berger (2011, page 216) also contends that "research should continue to build on the recent work of Johnston et al. (2009) and De Franco et al. (2009) by further considering the role of debt analysts in the firm's information environment."

Several recent studies explore the role of bond analysts in the market. Johnston, Markov, and Ramnath (2009) examine the *determinants* of bond analysts' debt reports. They find that bond analysts' decisions to issue debt reports depend on costs and benefits of providing the information to the market. De Franco, Vasvari, and Wittenberg-Moerman (2009) and Gurun, Johnston, and Markov (2011) examine the *impact* of debt research on both debt and equity markets. De Franco et al. (2009) find that trading volume and abnormal returns change following the provision of bond analysts' recommendations in both debt and equity markets, suggesting that both markets react to bond analysts' recommendations. Gurun et al. (2011) conclude that bond analysts' debt reports enhance the bond market efficiency by both increasing the bond price adjustment speed and increasing the total information available in the market. On the other hand, De Franco, Vasvari, Vyas, and Wittenberg-Moerman (2014) find that the value of debt reports is driven mainly by bond analysts' unique view on debt-equity conflict events, such as M&A activities, stock repurchase, or spin-off and that the bond market reaction is stronger than the equity market reaction when debt analysts' view is different from equity analysts' view.

[6] "Investing solely or mainly on the basis of rating-agency bands has become an almost useless strategy" (Peter, 2002).

Many bond analysts provide forecasts on cash flows and earnings in their debt reports. Malmendier and Shanthikumar (2007) document that recommendations have the most impact on the trading behavior of small traders, but that (equity) analyst earnings forecasts affect the trading behavior of large traders. Consistent with this, Mikhail, Walther, and Willis (2007) find that, while small investors are able to incorporate the information in a coarse and easily interpreted signal (i.e., the recommendation revision), they appear unable or uninterested in extracting the information in the more complex signal (i.e., the earnings forecast revision). Since most bond investors are institutional investors (i.e., large investors), information on cash flow and earnings forecasts, compared to bond recommendations, is particularly important for bond investors.[7] Despite the importance of the informational role of bond analysts' cash flow and earnings forecasts in the bond market, prior literature has paid little attention to forecasts issued by bond analysts. My study fills this gap by examining the properties of bond analysts' forecasts on the firm's future performance.

Sell-side bond analysts' forecasts are manually-collected from debt reports provided by *Investext* for the period 2001-2010. My first findings show that the likelihood to issue cash flow forecasts is greater for bond analysts than for equity analysts, whereas the probability to issue earnings forecasts is greater for equity analysts than for bond analysts, implying that cash flow (earnings) information is more (less) important to bond investors than to stock investors and hence to bond analysts than to equity analysts. Next, I compare the bias and accuracy of the earnings and cash flow forecasts for both bond analysts and equity analysts. The results show that bond analysts are less optimistic in both cash flow and earnings forecasts than equity analysts, suggesting that bond analysts have a more conservative view on company's future

[7] This is also consistent with Malmendier and Shanthikumar (2014)'s argument that the upward bias in (equity) analysts' recommendations are likely to be corrected by large investors where (equity) analysts, who are fear of tarnishing reputations with large investors, are likely to provide relatively unbiased earnings forecasts.

performance than equity analyst with respect to both earnings and cash flow forecasts, which may be driven by bond investors' asymmetric demand for good news and bad news. In addition, bond analysts' cash flow (earnings) forecasts are more (less) accurate than equity analysts' cash flow (earnings) forecasts, which again corroborates my first finding of the greater importance of cash flows (earnings) to bond (equity) investors and analysts. Finally, I examine the determinants of bond analysts' forecasts on cash flows and earnings. I find that bond analysts are more likely to issue cash flow forecasts for firms with greater volatility of cash flows and under more severe liquidity constraint. These results suggest that bond analysts are striving to meet bond investors' demand for future cash flows information, especially when the uncertainty and constraint on cash flows are severe. I also find that bond analysts are more likely to provide earnings forecasts along with cash flow forecasts for firms with greater accruals volatility and with lower earnings.

This study contributes to the literature in two important ways. First, my study contributes to the recent growing literature that examines the informational role of bond analysts. Despite that majority of bond traders are institutional investors, bond analysts' cash flow and earnings forecasts, one of the most important components in bond analysts' reports, have been neglected by academic researchers. To my knowledge, my study is the first to document bond analysts' efforts on forecasting firms' future cash flows and earnings. Second, this paper also supplements the literature on the properties of equity analysts' forecasts. My findings suggest that the properties of bond analysts' forecasts are quite different from those of equity analysts' forecasts. In particular, as regards to the debate on the quality of analysts' cash flows forecasts literature (e.g., Givoly, Hayn, and Lehavy, 2009; Call, Chen, and Tong, 2013), my study provides evidence supportive of Givoly et al. (2009), who argue the quality of *equity* analysts' cash flow forecasts is limited.

The paper proceeds as follows. The next section discusses the institutional context of the bond market and bond analysts' activities, reviews the related literature, and develops my hypotheses. Section 3 explains the research design and Section 4 describes the nature of my sample and discusses summary statistics. Section 5 reports the main empirical results. Finally, Section 6 summarizes the findings of the paper and concludes with the discussion on their economic implications.

2. Institutional Background, Literature Review, and Hypothesis Development

2.1. Institutional background: Role of bond analysts

There are several differences between bond and equity markets. First, the bond market, especially the U.S. debt market, is less transparent and less liquid compared to the stock market (e.g., Kwan, 1996; Hong and Warga, 2000; Hotchkiss and Ronen, 2002; Downing, Underwood, and Xing, 2009; De Franco et al., 2009). Second, most of the bond investors are institutional investors, thus the degree of sophistication of investors is relatively high. Lastly, because bondholders receive less value when firms' total value of assets become less than the total amount of debt, nor do they fully receive the benefit when firms earn large profits or earnings, bond investors have an asymmetric demand for information about firm's prospect and future performance. Consistent with this, Easton, Monahan, and Vasvari (2009) examine the association between *bond returns* and news proxied by *earnings surprises* at the earnings announcement. While they find significant bond market reactions to both good news and bad news, the magnitude of reactions is greater for bad news than for good news.

Debt analysts play pervasive and significant roles in the capital market. Similar to equity analysts, debt analysts issue not only buy/hold/sell recommendations on the debt security but also forecasts on future performance (e.g., earnings and cash flows).[8] Further, both debt analysts and equity analysts are subject to Regulation Fair Disclosure (“Reg. FD”) and Regulation Analyst Certification (“Reg. AC”). However, since they are analyzing different securities, they differ in many aspects. First, debt analysts are more likely to cover risker firms compared to stock analysts (Johnston et al., 2009; De Franco et al., 2009) whereas stock analysts are more likely to follow firms which have greater growth potential and visibility (Bhushan, 1989). Second, debt analysts also provide an analysis of potential impact of *debt-specific* risk events, including stock repurchases, divestments of assets, spin-offs, leverage buyouts, and debt-funded acquisitions (De Franco et al., 2014). Since the benefits and risks facing these events are different for bondholders and shareholders, debt analysts’ interests in these events drive unique characteristics of debt reports.[9]

2.2. Literature review

Johnston et al. (2009) find that 1) bond analysts tend to cover firms with a higher probability of financial distress, 2) debt analysts’ coverage increases with the total amount of debt issued, 3) firms with a higher market-to-book ratio are less covered by bond analysts, 4) firms with greater leverage receives more debt research, and 5) the *stock* market reacts strongly when debt analysts issue negative news but does not react when they issue positive news. De Franco et al. (2009) examine characteristics of debt analysts’ bond recommendations and market consequences of their recommendations in both *equity* and *bond* markets. First, they find that the distribution of recommendations is positively skewed (i.e. more buy recommendations than sell

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[8] Bond analysts, as well as equity analysts, attend to conference calls and *All-America Institutional Investor* selects the best bond analysts across industries each year (Kandler, 2001; Ronan, 2006). For more detailed information about debt analysts’ activities, please see Kandler (2001), Peter (2002), and Ronan (2006).

[9] While credit rating agencies also provide company-level and debt-level research reports, unlike credit rating agencies debt analysts identify undervalued/overvalued debt and forecast a firm’s upcoming credit rating change and future profitability. Consistent with this, Johnston et al. (2009) and DeFranco et al. (2009) provide evidence that debt analysts issue more timely reports than CRAs.

recommendations), similar to that of equity analysts' recommendations. Second, the bond market reaction, measured by both volume and price change, to bond recommendations is economically and statistically significant. Third, the market reaction to bond recommendations leads credit rating agencies reports. In conclusion, they provide evidence that bond analysts' recommendations provide incremental information to the market, thus enhancing the information efficiency of the corporate bond market. Gurun et al. (2011) corroborates De Franco et al. (2009)'s results. They find that debt analysts' research lessens the lead-lag relationship between equity market and bond market documented by previous studies (Kwan, 1996; Hotchkiss and Ronen, 2002; Downing, Underwood, and Xing, 2009). Furthermore, they also find an increase in information efficiency driven by bond analysts in the bond market and that the increase is more likely due to bond analysts' efforts to increase the speed of price adjustment than to expand the total information set to the market. De Franco et al. (2014) provide a more in-depth investigation into the informational role of bond analysts. Using a computational linguistic program to code debt analysts' tones on debt-specific events, they find that the bond market reaction to debt analysts' tones in their reports increases with debt analysts' negative discussions of conflict events.

A large body of studies has examined the determinants and properties of equity analysts' forecasts. Bhushan (1989) finds that equity analysts follow larger firms, firms with larger stock return variability, firms that have fewer lines of business, and firms whose returns are more correlated to the market return. DeFond and Hung (2003) find that equity analysts' cash flow forecasts are more demanded by equity investors for firms with 1) larger accruals, 2) more heterogeneous accounting choices, 3) higher past earnings volatility, 4) higher capital intensity, and 5) poorer financial health. The quality of equity analysts' earnings forecasts has been extensively studied during the late 1970s and 1980s (for example, see Brown and Rozeff, 1978; Fried and Givoly, 1982; Brown, Griffin, Hagerman, and Zmijewski, 1987). Givoly, Hayn, and Lehavy (2009) document that the quality of equity analysts' cash flow forecasts does not substantially dominate the quality of time-series cash flows forecast models, arguing that analysts simply add depreciation and amortization to their earnings forecasts to derive their cash flow forecasts. In contrast, others believe that equity analysts' cash flow forecasts are not naïve extensions from their earnings forecasts (Call, 2008; Call, Chen, and Tong, 2009, 2013; McInnis and Collins, 2011). For example, Call et al. (2013) manually collect samples of full-text equity analysts' reports and find that they, indeed, explicitly forecasts working capitals in order to form their cash flow forecasts.

Similar to equity analysts, bond analysts provide forecasts on firm's future operating performance, such as earnings, operating income (EBIT), earnings before interest, tax, and depreciation and amortization (EBITDA), operating cash flows, or free cash flows. However, prior studies have paid little attention to bond analysts' forecast behaviors despite the fact that most bond investors are institutional investors for whom cash flow and earnings forecasts are particularly important information sources. Further, although *bond* analysts' incentives to issue cash flow and earnings forecasts are expected to be different from those of *equity* analysts, prior studies have not compared forecast properties between bond analysts' and equity analysts' cash flow or earnings forecasts. In the following section, I develop my hypotheses to examine these issues.

2.3. Hypothesis development

Although both cash flow and earnings information is important to bond investors, the stability of future cash flow patterns is the first-order concern for bond investors because, unlike equities, the payment of debt securities (i.e., principal and interests) is fixed and their maturity is finite. While earnings information is also important to bondholders for contracting purposes (Watts and Zimmerman, 1986; DeFond and Jiambalvo, 1994), bondholders' wealth is more sensitive to cash flow information than to earnings information. I therefore posit that bond investors are more likely to demand cash flow information than for earnings information.[10] Meanwhile, earnings information is the most important source to equity investors for both valuation (Ball and Brown, 1968; Dechow, 1994; Ohlson, 1995) and contracting purposes (Watts and Zimmerman, 1986, Sloan, 1993) although cash flow information is incrementally valuable information to stock investors (DeFond and Hung, 2003). Consequently, earnings are more likely to be the primary interest to equity analysts.[11]

Therefore, the relative emphasis on cash flows and earnings is likely to differ between bond analysts and equity analysts. Specifically, I argue that cash flows are the primary concern of bond analysts whereas earnings are the main interest to equity analysts. Based on these arguments, I advance the following hypothesis:

H1a: Ceteris Paribus, bond analysts are more likely to issue cash flow forecasts than equity analysts.

H1b: Ceteris Paribus, equity analysts are more likely to issue earnings forecasts than bond analysts.

A vast majority of prior research documents that equity analysts are optimistically biased. Analysts have incentives to issue optimistic forecasts in order (1) to win lucrative investment

[10] Consistent with this argument, McEnroe (1996) reports survey results that accounting professionals, such as financial analysts, investment advisors, accounting professors and accountants, view debt investors as the main beneficiaries of cash flow information. Edmonds et al. (2011) suggest that cash flow forecasts are important for bondholders.

[11] I randomly selected 50 full-text reports in *Investext* and find that almost every *equity* report contains an earnings forecast whereas about 60% of equity reports include cash flow forecasts, which is similar to the finding by Call (2008).

banking business (Lin and McNichols, 1998), (2) to retain access to management (Lim, 2001), and (3) to increase equity trading commissions (Irvine, 2004). Consistent with this, De Franco et al. (2009) find that bond analysts more frequently issue buy *recommendations* than sell recommendations. Hence, I expect that the distribution of bond analysts' *forecasts* will be skewed to the right as well. However, since bond investors, compared to equity investors, are more concerned about downside risk, such as negative surprise of actual cash flows and earnings, which could be caused by preceding inflated forecasts, I argue that potential benefits of issuing optimistic forecasts are smaller for bond analysts than for equity analysts.[12] Based on these arguments, I propose that bond analysts provide more conservative (i.e., less optimistic) forecasts than equity analysts:

H2: Ceteris Paribus, bond analysts' forecasts on cash flows and earnings are less optimistic than equity analysts' forecasts on cash flows and earnings, respectively.

If bond analysts, compared to equity analysts, tend to provide less optimistic cash flow and earnings forecasts to serve the demand of bondholders (H2), the smaller optimistic bias implies a more leftward pattern in the distribution of signed forecast errors (i.e., forecasted minus actual cash flows or earnings) for bond analyst forecasts than for equity analyst forecasts. I note that such a pattern can be composed of both (i) a smaller positive forecast error toward zero error for bond analyst forecasts than for equity analyst forecasts and (ii) a larger negative forecast error from (near) zero error toward negative error for bond analyst forecasts than for equity analyst forecasts. In the former case, it is obvious that bond analyst forecasts are more accurate

[12] This conjecture is consistent with the finding by Easton et al. (2009), who provide evidence that bond investors react more strongly to bad news than to good news and thus bond analysts are more sensitive to bad news than equity analysts. In addition, although De Franco et al. (2009) document that bond analysts' view is more conservative than that of equity analysts using recommendations, it is not clear, a priori, whether bond analysts' forecasts are less optimistic than equity analysts' forecasts, given the fact that the degree of individual analysts' optimism in recommendations and forecasts could differ (Malmendier and Shanthikumar, 2007, 2014; Mikhail et al., 2007).

than equity analyst forecasts but in the latter case it is possible that bond analyst forecasts are less accurate than equity analyst forecasts.

In H1a and H1b, I argue that bond analysts, relative to equity analysts, are more likely to provide cash flow forecasts than earnings forecasts to meet the strong demand of bondholders for future cash flow information. Since cash flows are the key focus of their forecast activities (McEnroe, 1996; Edmonds, Edmonds, and Maher, 2011; Mangen, 2013), bond analysts are likely to put considerable efforts in their research to provide high quality cash flow forecasts. Therefore, I posit that bond analysts' cash flow forecasts are more accurate than those of equity analysts. In contrast, I expect earnings forecasts are less of concerns for bond analysts than for equity analysts. Based on this conjecture, I offer the following hypothesis:

H3: Ceteris Paribus, bond analysts' forecasts on cash flows (earnings) are more (less) accurate than equity analysts' forecasts on cash flows (earnings).

To better understand why bond analysts *per se* would forecast cash flows and earnings, it is important to identify the economic determinants that are likely to drive bond investors' demand on both forecast information. Bond investors' demand for information on future cash flows will be stronger when a firm's ability to pay its debt obligation is more doubtful. Since the stability of future cash flow patterns is a critical concern for bondholders, bond investors are more likely to demand for cash flow information for firms with higher volatility in cash flows (i.e. firms with higher uncertainty in future cash flows). I also conjecture that firms under liquidity constraint will generate more concerns regarding the viability of the firm than other firms (Sundram and Yermack, 2007; Cassell, Huang, Sanchez, and Stuart, 2012), causing stronger demand for cash flow forecasts.

However, since accruals, along with cash flows, play a positive role in explaining future performance of the firm (Dechow, 1994; Dechow, Kothari, and Watts, 1998; Barth, Cram, and Nelson, 2001), some bond analysts will not only provide cash flow forecasts but also earnings forecasts. In fact, Easton et al. (2009) provide evidence on bond market reaction to earnings surprises around earnings announcements. I therefore argue that although bond analysts are less concerned about earnings relative to cash flows, earnings still provide relevant information about a firm's ability to generate future cash flows particularly when the volatility or uncertainty of its accruals is high and when the firm is subject to lower or negative earnings performance.[13] Based on these arguments, I advance the following hypothesis:

H4a: Ceteris Paribus, bond analysts are more likely to provide cash flow forecasts for firms a) with greater volatility of cash flows and b) under more severe liquidity constraint.

H4b: Ceteris Paribus, bond analysts are more likely to provide earnings forecasts along with cash flow forecasts for firms a) with greater volatility of accruals, and b) with lower earnings.

3. Research Design

3.1. Propensity to issue cash flow and earnings forecasts for bond analysts versus equity analysts (*H1a and H1b*)

H1a (H1b) predicts that the probability to issue cash flow (earnings) forecasts is greater (smaller) for bond analysts than for equity analysts. In order to test this prediction, I estimate the following logistic regression model for firms covered by bond analysts and equity analysts, where year fixed effects are included and the standard errors are clustered by firm (Petersen, 2009):

$$Prob\ (CF1\_F_{it}=1) = G\ (\alpha_0 + \alpha_1 BondDummy_{it-1} + \alpha_2 CFOVOL_{it-1} + \alpha_3 CFO_{it-1} + \alpha_4 ABSACC_{it-1} + \alpha_5 CAPINT_{it-1} + \alpha_6 ALTMAN_{it-1} + \alpha_7 SIZE_{it-1} + \varepsilon_{it-1}) \qquad (1\text{-}1)$$

[13] In contrast, prior studies find *equity* analysts are more likely to cover firms with *higher* earnings performance than those with lower earnings performance (Yu, 2008).

$$Prob\ (EARN\_F_{it}=1) = G\ (\alpha'_0 + \alpha'_1 BondDummy_{it-1} + \alpha'_2 EARNVOL_{it-1} + \alpha'_3 EARN_{it-1} + \alpha'_4 SIZE_{it-1} + \varepsilon_{it-1}) \qquad (1\text{-}2)$$

All observations are represented at firm-year level and must have at least one annual cash flow or earnings forecast available. All independent variables are measured in the year prior to the forecast year. The dependent variable, *CF1_F*, is an indicator variable that equals one if either bond analysts or equity analysts issue at least one forecast on operating cash flows (CFO) or free cash flows (FCF) during the fiscal year, and zero otherwise. *EARN_F* equals one if either bond analysts or equity analysts issue at least one forecast on earnings (i.e., income before extraordinary items) during the fiscal year, and zero otherwise. The main variable of interest, *BondDummy*, is an indicator variable, which equals one if the forecast is issued by bond analysts, and zero otherwise (i.e. if the forecast is issued by equity analyst). In the context of H1a and H1b, I expect α_1 to be *positive* and α'_1 to be *negative*, which indicate that, the probability of issuing cash flow (earnings) forecasts is greater for bond (equity) analysts than for equity (bond) analysts.

In regression model (1-1), I control for the factors that are expected to affect analysts' incentive to issue cash flow forecasts.[14] I first include a proxy for future cash flow uncertainty (*CFOVOL*), which is measured as the firm-specific standard deviation of the operating cash flows divided by average assets. Previous seven years are used to calculate the standard deviation with the minimum requirement of three years. *CFO*, a proxy for degree of the liquidity constraint, is also controlled, calculated as operating cash flows divided by average total assets. I expect α_2 to be *positive* and α_3 to be *negative*, indicating that when the uncertainty about cash

[14] Later, bond analysts' incentive to issue cash flow forecasts is formally advanced as a hypothesis in H4a.

flows is high and when the liquidity constraint is severe, the probability of analysts issuing cash flow forecasts is higher.

Next, I control for the determinants of analysts' provision of a cash flow forecast following the previous literature (e.g., DeFond and Hung, 2003), which shows that *equity* analysts are more likely to issue cash flows forecasts for firms with (1) high earnings volatility[15], (2) large absolute accruals, (3) high capital intensity, (4) poor financial health, and (5) heterogeneous accounting choices relative to their industry peers[16], consistent with the notion that analysts are providing additional value-relevant information particularly when earnings are less useful in stock valuations. *ABSACC* is defined as the absolute value of earnings minus operating cash flows divided by average total assets. Earnings are income before extraordinary items. *CAPINT* is *g*ross property, plant, and equipment (Gross PP&E) divided by total sales in the previous year. Following Altman (1968), *ALTMAN* = 1.2 (Net working capital / Total Assets) + 1.4 (Retained earnings / Total Assets) + 3.3 (Earnings before interest and taxes / Total Assets) + 0.6 (Market value of equity / Book value of liabilities) + 1.0 (Sales / Total Assets). Consistent with DeFond and Hung (2003), α_4 and α_5, are expected to be *positive*, while α_6 is expected to be *negative*. Prior literature finds that firm size (*SIZE*) proxies for firm risk and information environment. *SIZE* is calculated as the natural logarithm of the equity market capitalization.

In regression model (1-2), I control for variables that are expected to affect analysts' incentive to issue earnings forecasts.[17] *EARNVOL*, a proxy for uncertainty of earnings performance, is the firm-specific standard deviation of the earnings before extraordinary items

[15] I drop *EARNVOL* in model (1-1) since the correlation between *EARNVOL* and *CFOVOL* is high (ρ = 0.35). Nevertheless, when I include *EARNVOL*, the coefficient on *BondDummy* is still positive (coeff. = 0.443, t-stat = 2.65).

[16] Accounting choice heterogeneity is the relative difference between the firm and industry group firms with respect to 1) inventory valuation method, 2) investment tax credit, 3) depreciation, 4) successful-efforts vs. full-cost for oil and gas companies, and 5) purchase vs. pooling method for M&A firms. To maintain a reasonable sample size, I do not control for the accounting choice heterogeneity in the main regression.

[17] Again, bond analysts' incentive to issue earnings forecasts is formally advanced as a hypothesis in H4b.

divided by average assets. Previous seven years are used to calculate the standard deviation with the minimum requirement of three years. *EARN*, a proxy for earnings performance, is calculated as earnings before extraordinary items divided by average total assets. I expect α'_2 to be *positive* and α'_3 to be *negative*, indicating that when the uncertainty about earnings is high and when earnings performance is low, the probability of bond analysts issuing earnings forecasts is higher.

3.2. The bias in cash flow and earnings forecasts for bond analysts versus equity analysts (H2)[18]

To compare the degree of forecast bias between bond and equity analysts' forecasts, I calculate the bias as the signed difference between per-share forecasted and actual values, deflated by the actual value.

$$Bias_{it} = (F_{it} - A_{it}) \,/\, |A_{it}| \tag{2}$$

A_{it} is the actual value per share for firm i and year t[19], and F_{it} is the (consensus) forecasted value per share for firm i and year t. The performance measure in this analysis is restricted to operating cash flows (CFO), EBITDA, and earnings before extraordinary items (EARN). Although bond analysts provide forecasts of free cash flows (FCF) and earnings before interest and tax (EBIT), these forecast items are not available for equity analysts on I/B/E/S. I thus do not use these forecasts in bias and accuracy (next section) analyses.

To calculate each of bond and equity analysts' consensus forecasts, I use the most recent forecast for each analyst for each firm-year. I then calculate the median consensus forecasts for

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[18] It is possible that bond analysts' forecasts are simply mimicking equity analysts' forecasts. However, this is not an issue because based on randomly selected full-text bond and equity analysts' reports I observe that earnings and/or cash flow forecasts issued on the same date by the same investment bank differ between bond and equity analysts (See Appendix B).

[19] I obtain qualitatively similar results when it is deflated by beginning-of-period or end-of-period price per share, which is discussed in section 5.4.2.

each firm-year, separately for bond analysts and equity analysts.[20] I first hand-collect the actual value from individual bond reports. If the actual value is missing in bond reports, then the actual value from I/B/E/S (for each *CFO*, *EBITDA*, or *EARN*) is used instead.[21] Next I compare the bias of forecasts between different groups (i.e., bond analysts versus equity analysts). This procedure ensures that the forecast error difference between bond analysts and equity analysts are not due to any alternative definition of actual or forecast values but to their different forecasting abilities (see Bradshaw and Sloan, 2002; Bhattacharya, Black, Christensen, and Larson,, 2003; Abarbanell and Lehavy, 2007).

I test H2 with the following regression models, with year fixed effects included and standard errors clustered by firm:

$$\begin{aligned} Bias\_CFOF_{it} = {} & \beta_0 + \beta_1 (BondDummy)_{it} + \beta_2 (CFOVOL)_{it} + \beta_3 (CFO)_{it} + \beta_4 (HORIZON)_{it} \\ & + \beta_5 (SIZE)_{it} + \beta_6 (BM)_{it} + \beta_7 (LEV)_{it} + \varepsilon_{it} \end{aligned} \tag{3-1}$$

$$\begin{aligned} Bias\_EBITDAF_{it} = {} & \beta'_0 + \beta'_1 (BondDummy)_{it} + \beta'_2 (EBITDAVOL)_{it} + \beta'_3 (EBITDA)_{it} \\ & + \beta'_4 (HORIZON)_{it} + \beta'_5 (SIZE)_{it} + \beta'_6 (BM)_{it} + \beta'_7 (LEV)_{it} + \varepsilon'_{it} \end{aligned} \tag{3-2}$$

$$\begin{aligned} Bias\_EARNF_{it} = {} & \beta''_0 + \beta''_1 (BondDummy)_{it} + \beta''_2 (EARNVOL)_{it} + \beta''_3 (EARN)_{it} \\ & + \beta''_4 (HORIZON)_{it} + \beta''_5 (SIZE)_{it} + \beta''_6 (BM)_{it} + \beta''_7 (LEV)_{it} + \varepsilon''_{it} \end{aligned} \tag{3-3}$$

In the above three equations, the dependent variables are forecast bias (*Bias*) for CFO (*Bias_CFOF*), EBITDA (*Bias_EBITDAF*), and EARN (*Bias_EARNF*), respectively. The variable of interest in each of the three equations, *BondDummy*, is an indicator variable, which

[20] I use the *median* consensus forecasts because Abarbanell and Lehavy (2003) find that using *mean* forecast errors may lead to incorrect inference due to extreme forecast errors. Nonetheless, using either mean consensus forecasts or the last forecasts does not alter my inferences, and the results are reported in Section 5.4.2.

[21] The actual and forecast value collected from bond reports are in total amount (million). Since I/B/E/S data are all in per share value, I deflate the value in bond data by the number of primary or diluted shares in Compustat, which facilitates the comparison between bond and equity analysts' values (Livnat and Mendenhall, 2006).

equals one if the forecast is issued by the bond analyst, and zero otherwise (i.e. if the forecast is issued by equity analyst). Since *Bias* is the signed forecast error, a *positive* value of *Bias* means that the analyst forecast is *optimistic*, and a *negative* value of *Bias* represents that it is *pessimistic*. I conjecture that bond (equity) analyst forecasts are less (more) optimistic than equity (bond) analyst forecasts for both cash flows and earnings. Accordingly, I expect β_1, β'_1, and β''_1 to be *negative.*

Note that I define cash flows in a broader definition which includes EBITDA as well as CFO. EBITDA differs from earnings and operating cash flows because it eliminates the effects of financing and accounting decisions by excluding payments for taxes or interest as well as capital expenditures and depreciation. EBITDA also differs from free cash flows because it excludes cash requirements for replacing capital assets. However, since 1) EBITDA was used to indicate the ability of a company to service debt, 2) the amount of depreciation and amortization expenses comprises a substantial amount of total accruals (Dechow, 1994), and 3) the correlation (ρ = 0.757) between bond analysts' EBITDA and Compustat CFO ("OANCF") is significantly greater than the correlation (ρ = 0.277) between bond analysts' EBITDA and Compustat EARN ("IB"), EBITDA is considered cash flows rather than earnings, particularly for *bondholders* and *bond analysts*.[22,23]

HORIZON is defined as the number of days between the earnings announcement date and the forecast issuance date. Since analysts' optimistic forecasts are walked down by the management (Bartov, Givoly, and Hayn, 2002; Matsumoto, 2002; Cotter, Tuna, and Wysocki,

[22] Historically, EBITDA first came into common use with leveraged buyouts (LBO) in the 1980s. In LBOs, the key factor is cash generated by the firm prior to discretionary expenditures, as it is this cash that the buyer will use to pay off the loans he or she used to purchase the firm, and EBITDA is the measure of cash flows from operations that can be used to support debt payment at least in the short term.

[23] In section 5.4.1., I use only the cases where EBITDA is not merely including taxes, interest, and depreciation and amortization but involving explicitly adjusting working capitals, and the results are qualitatively similar (See table 11).

2006; Kross, Ro, and Suk, 2011; Kwak, Ro, and Suk, 2012), the coefficient on *HORIZON* is expected to be *positive*. I also control for the volatility and the level of cash flows (or earnings). *CFOVOL* (*CFO*), *EBITDAVOL* (*EBITDA*), and *EARNVOL* (*EARN*) are included in equations (3-1) – (3-3), respectively. Finally, *BM* and *LEV* are controlled for in the regression models. *BM* is calculated as book value of equity divided by market value of equity. *LEV* equals the book value of debt divided by the book value of equity. The rest of the variables are defined in the same way as in regression models (1-1) and (1-2).

3.3. The accuracy of cash flow and earnings forecasts between bond analysts versus equity analysts (*H3*)

In order to compare forecast accuracy between bond and equity analysts' cash flow forecasts and earnings forecasts, I calculate forecast accuracy by multiplying forecast error (i.e., the absolute value of forecast bias) by -1:

$$Accuracy_{\mathrm{it}} = (-1) \times |F_{\mathrm{it}} - A_{\mathrm{it}}| \,/\, |A_{\mathrm{it}}| \tag{4}$$

A_{it} and F_{it} are defined as in equation (2). In order to test H3, I estimate the following regressions similar to those in Section 3.2:

$$\begin{aligned} Accu\_CFOF_{\mathrm{it}} = {} & \gamma_0 + \gamma_1 (BondDummy)_{\mathrm{it}} + \gamma_2 (CFOVOL)_{\mathrm{it}} + \gamma_3 (CFO)_{\mathrm{it}} + \gamma_4 (HORIZON)_{\mathrm{it}} \\ & + \gamma_5 (SIZE)_{\mathrm{it}} + \gamma_6 (BM)_{\mathrm{it}} + \gamma_7 (LEV)_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \end{aligned} \tag{5-1}$$

$$\begin{aligned} Accu\_EBITDAF_{\mathrm{it}} = {} & \gamma'_0 + \gamma'_1 (BondDummy)_{\mathrm{it}} + \gamma'_2 (EBITDAVOL)_{\mathrm{it}} + \gamma'_3 (EBITDA)_{\mathrm{it}} \\ & + \gamma'_4 (HORIZON)_{\mathrm{it}} + \gamma'_5 (SIZE)_{\mathrm{it}} + \gamma'_6 (BM)_{\mathrm{it}} + \gamma'_7 (LEV)_{\mathrm{it}} + \varepsilon'_{\mathrm{it}} \end{aligned} \tag{5-2}$$

$$\begin{aligned} Accu\_EARNF_{\mathrm{it}} = {} & \gamma''_0 + \gamma''_1 (BondDummy)_{\mathrm{it}} + \gamma''_2 (EARNVOL)_{\mathrm{it}} + \gamma''_3 (EARN)_{\mathrm{it}} \\ & + \gamma''_4 (HORIZON)_{\mathrm{it}} + \gamma''_5 (SIZE)_{\mathrm{it}} + \gamma''_6 (BM)_{\mathrm{it}} + \gamma''_7 (LEV)_{\mathrm{it}} + \varepsilon''_{\mathrm{it}} \end{aligned} \tag{5-3}$$

The dependent variables are forecast accuracy (*Accuracy*) for CFO (*Accu_CFOF*), EBITDA (*Accu_EBITDAF*), and EARN (*Accu_EARNF*), respectively. Because I multiply all the forecast accuracy measures by -1, a *larger* value indicates a *more accurate* forecast, and a *smaller* value indicates a *less accurate* forecast. Following H3, I expect both γ_1 and γ'_1 to be *positive*, and γ''_1 to be *negative*, indicating that bond (equity) analysts are more accurate forecasting cash flows (earnings).[24]

The rest of the variables are defined as in equations (3-1) – (3-3). I include *CFOVOL*, *EBITDAVOL*, and *EARNVOL* in equations (5-1) – (5-3), respectively, to control for analysts' inherent difficulty in forecasting firm's cash flows or earnings because the dependent variables in the three models represent different performance measures. The coefficients on *CFOVOL*, *EBITDAVOL*, and *EARNVOL* are predicted to be *negative*, suggesting that, as the uncertainty of future performance is greater for either cash flows or earnings, analysts' forecasting abilities deteriorate. I also include *HORIZON*, the number of days between analysts' forecast date and the actual announcement date for the firm followed by the analyst, in order to control for the age of each forecast. Since analysts' forecasting abilities improve as their forecast dates become closer to actual earnings announcement dates (Brown, 2001), the coefficient on *HORIZON* is expected to be *negative*. *SIZE* is expected to be positively associated with the accuracy because a greater size indicates a better informational environment. Finally, *BM* and *LEV* are controlled for in the regression models and expected to be negatively related to analysts' accuracy because they may represent for the inherent firm risk.

***3.4. Determinants of bond analysts' cash flow and earnings forecasts provision* (*H4a and H4b*)**

[24] Note, however, that in table 6 (univariate analysis) and figure 1 (intra-year change in forecasts), *accuracy* is not multiplied by -1.

In order to test H4a and H4b, I estimate the following logistic regression models only for firms covered by bond analysts, including year fixed effects and cluster-adjusted standard errors:

$$Prob\ (CF\_F_{\mathrm{it}} = 1) = G\ (\delta_0 + \delta_1 CFOVOL_{\mathrm{it-1}} + \delta_2 CFO_{\mathrm{it-1}} + \delta_3 LEV_{\mathrm{it-1}} + \delta_4 EARNVOL_{\mathrm{it-1}} + \delta_5 ABSACC_{\mathrm{it-1}} + \delta_6 CAPINT_{\mathrm{it-1}} + \delta_7 ALTMAN_{\mathrm{it-1}} + \delta_8 SIZE_{\mathrm{it-1}} + \delta_9 MB_{\mathrm{it-1}} + \delta_{10} DSIZE_{\mathrm{it-1}} + \delta_{11} IMR_{\mathrm{it-1}} + \varepsilon_{\mathrm{it-1}}) \quad (6\text{-}1)$$

$$Prob\ (EARN\_F_{\mathrm{it}} = 1) = G\ (\delta'_0 + \delta'_1 ACCVOL_{\mathrm{it-1}} + \delta'_2 EARN_{\mathrm{it-1}} + \delta'_3 ALTMAN_{\mathrm{it-1}} + \delta'_4 SIZE_{\mathrm{it-1}} + \delta'_5 MB_{\mathrm{it-1}} + \delta'_6 LEV_{\mathrm{it-1}} + \delta'_7 DSIZE_{\mathrm{it-1}} + \delta'_8 IMR_{\mathrm{it-1}} + \varepsilon_{\mathrm{it-1}}) \quad (6\text{-}2)$$

All observations are represented by firm-year level variables, and all independent variables are measured in the year prior to the forecast year. I identify bond analysts' issuance of cash flow forecasts in two different ways. If bond analysts issue any forecast of operating cash flows (CFO) or free cash flows (FCF) then *CF1_F* equals one, and zero otherwise. Alternatively, *CF2_F* equals one if bond analysts provide CFO, FCF, or earnings before interests, taxes, depreciation, and amortization (EBITDA) for firm i and year t, and zero otherwise, where cash flows are in a broader manner.

In regression model (6-1), the variables of my interest are *CFOVOL* and *CFO*. In the context of H4a, I expect δ_1 to be *positive* and δ_2 to be *negative*, which indicate that, as the volatility of cash flows and the liquidity constraint are greater, the probability of bond analysts issuing cash flow forecasts is higher.

I first control for the agency cost of debt because the presence of a conflict between shareholders and bondholders (Jensen and Meckling, 1976) induces the agency cost of debt in which bondholders, who are typically interested in a less risky investment, may want to place restrictions on the use of their money to reduce their risk. Bondholders with greater agency costs of debt are therefore more likely to demand information about future cash flows. Because firms with a higher leverage (*LEV*) place restrictions on the use of their money, these firms face greater agency costs of debt and thus are more likely to demand information about future cash flows. I expect δ_3 to be *positive*, indicating that as the agency cost of debt is the greater, the probability of bond analysts issuing cash flow forecasts is higher. Similar to regression model (1-1), I control for the determinants (i.e., *EARNVOL*, *ABSACC*, *CAPINT*, *ALTMAN*, and *SIZE*) of equity analysts' provision of a cash flow forecast following the previous literature (i.e., DeFond and Hung, 2003). Next, following Johnston et al. (2009), I control for market-to-book ratio and debt size.[25] *MB* equals equity market value divided by equity book value, which proxies for either 1) growth opportunity or 2) financial distress as noted in Johnston et al. (2009). Therefore, the sign of coefficient on *MB* (δ_9) is not unambiguous *a priori*. *DSIZE* is the natural logarithm of book value of debt. Consistent with Johnston et al. (2009), δ_{10} is expected to be positive.[26]

Finally, since my sample on bond analysts' debt reports collected from *Investext* may not represent the (unobservable) population, relying solely on *Investext* as the source of debt analysts' reports is not completely free from the selection bias, although *Investext* is the only source available for debt analysts' information. This may be due to the possibility that debt analysts have less incentive to provide their reports to *Investext* than equity analysts (Ronan, 2006; Gurun et al., 2011). To mitigate any potential sample selection bias, I estimate a probit regression designed to capture the determinants of bond analysts' reports. Specifically, I regress bond analysts' probability to issue bond reports on determinants identified from Johnston et al. (2009), such as *SIZE*, *MB*, *LEV*, *INTCOV*, and *DSIZE*. From this probit estimation, I calculate an Inverse Mills Ratio (*IMR*) and then include this ratio in equation (6-1) and later in equation (6-2).

[25] If interest coverage is included, instead of *ALTMAN*, to control for the financial distress, the coefficient on *INTCOV* is negative and statistically significant at the 1% level (coeff.=-0.665, z-stat = -3.14).

[26] Although individual bond analyst characteristics (e.g., experience, available resource, complexity, etc.) could affect the decision to issue forecasts (Clement, 1999), the limitation on time-series and cross-sectional data does not allow me to calculate bond analysts' characteristics in a meaningful way.

In regression model (6-2), the dependent variable, *EARN_F*, is an indicator variable which equals one if bond analysts forecast earnings (income before extraordinary items), and zero otherwise. All firm-year observations must have at least one cash flow forecast. Corresponding to equation (6-1), I separately estimate equation (6-2) either when the sample is based on *CF1_F* = 1 or when *CF2_F* = 1. The variables of interest are *ACCVOL* and *EARN*.[27] *ACCVOL* is the firm-specific standard deviation of the total accruals divided by average assets. Total accruals are calculated as the difference between income before extraordinary items and operating cash flows. Previous seven historical years are used to calculate the standard deviation with the minimum requirement of three years. Given H4b, I predict that the coefficient on *ACCVOL*, δ'_1, to be *positive* and the coefficient on *EARN*, δ'_2, to be *negative*, which indicates that bond analysts are more likely to provide earnings forecasts when the accruals are highly volatile and when earnings are low. The rest of the variables are the same as defined previously.

4. Sample and Descriptive Statistics

4.1. Sample

Due to the lack of sell-side corporate debt reports on an archived database, I manually collect debt analysts' reports from *Investext*, a provider of full-text bond analysts' reports.[28] The sample period for bond analysts' reports spans from January 2001 to December 2010. The beginning year, 2001, was chosen to mitigate the effect of structural changes in analysts' forecasting behaviors driven by Reg FD (Kross and Suk, 2012), implemented in October, 2000.

Table 1 summarizes the sample selection process for bond reports. I search for debt analysts' reports using the following three criteria: 1) the asset class must be the fixed income, 2)

[27] Instead of *EARN*, I alternately use (i) Δ*EARN*, the change in income before extraordinary item (deflated by average total assets, or (ii) *LOSS*, a dummy variable which equals one if *EARN* is negative and zero otherwise. The (untabulated) results are qualitatively similar.

[28] *Investext* is now available in *Thomson ONE Banker*. *Investext also* provides full-text equity analysts' reports.

analysts' reports must be issued within the "North America" region, and 3) industrial-, geographic-, or macroeconomic-level research reports are excluded, thus only company-level reports are included in my sample. I also eliminate debt reports 1) for non-US firms, 2) for close-end funds, convertible bonds, or derivatives, 3) covering multiple companies within two days (see De Franco et al., 2009), 4) issued by equity analysts, and 5) issued by credit rating agencies, either certified (e.g. Moody's, Fitch) or non-certified (e.g. Morning Star, Rapid Ratings). After this initial screening process, I obtain 10,660 corporate bond reports, from which I collect issue dates of the reports, names of bond analysts, names of brokerage firms, names of firms followed, and the actual and forecasted earnings and/or cash flows, if available.[29] Then I manually match the names of the firms in bond reports with those of COMPUSTAT files. The final sample for testing H1a (H1b) includes 946 (997) firm-year observations for 392 (411) unique firms.

Equity analysts' actual and forecast values are collected from I/B/E/S Unadjusted Detail and Actuals Files, and company's financial variables are obtained from Compustat North America Fundamentals Annual File.

4.2. Descriptive statistics

Table 2 presents descriptive statistics on the characteristics of firms covered by bond analysts in my initial sample. In panel A, the number of bond reports, the number of firms, the number of annual forecasts, and quarterly forecasts are tabulated by fiscal year. On average, bond analysts issue 1,066 reports and cover approximately 360 firms every year. The coverage of bond analysts has slightly decreased after 2005, with an exception of 2008 (i.e., 1,234 bond

[29] The number of debt reports is 8,009 (between 1999 and 2004) in Johnston et al. (2009), and 28,378 (between 2002 and 2006) in De Franco et al. (2009). My conversations and correspondences with the authors of these papers and the researchers of *Thomson ONE Banker* indicate that a significant number of banks removed their own reports from the database. However, I do not see any *priori* reason that this selection issue would systematically bias my empirical findings.

reports).[30] The sudden increase in the bond analyst coverage in 2008 may reflect the recent credit crisis, which has triggered bond investors to demand more information on credit quality. Table 2, panel A also shows that the frequency of bond analysts' annual forecasts (3,863) is greater than that of their quarterly forecasts (2,378).

In panel B of table 2, I also compare the distribution of characteristics of firms covered by bond and firms covered by equity analysts. I search for all firms between 2001 and 2010 and calculate the firm characteristics at the firm-year level. Firms covered by bond analysts are larger than those followed by equity analysts. The average market value for BA firms is $10.61 billion whereas the average market value for EA firms is $5.50 billion. Consistent with Johnston et al. (2009), BA firms have higher leverage, lower interest coverage, larger debt size, and lower altman Z-score. In this full sample, BA firms are easier to forecast either cash flows or earnings than EA firms, since (historical) volatility of earnings, accruals, and operating cash flows are smaller for BA firms. The mean and median differences are all statistically significant at the 1% level. Therefore, it is important to control for the difference in inherent operating uncertainty between BA and EA firms when comparing the bias and accuracy between both analysts. Recall that I identify BA and EA samples based on propensity score matching technique. Panel C reports the firm characteristics difference based on the PS matched sample used for testing H1a. The mean (median) difference in all variables between BA and EA firms are all statistically insignificant, alleviating the concern that any difference in firm characteristics might drive my main results. Although I do not report descriptive statistics for other PS matched samples, for brevity, the results are similar to panel C.

[30] This is consistent with the conjecture that Trade Reporting and Compliance Engine (TRACE), which was introduced and expanded in 2005, acts as a substitute for debt research, thus possibly reduced the informational role of bond analysts (Bessembinder and Maxwell, 2008).

Table 3 presents descriptive statistics on bond analysts and their forecasts in my initial sample.[31] Panel A indicates that the most active brokerage firms issuing corporate bond reports are Deutsche Bank (38.81%), Bear Sterns and Co. Inc (11.78%), CIBC World Market Corp (11.46%), Morgan Stanley (7.81%), and JP Morgan (5.58%), comprising about 75.44% of my sample. 559 unique bond analysts are employed by brokerage houses. However, (untabulated) evidence reveals that more than half of the bond reports are issued by a team that comprises multiple sell-side bond analysts.[32]

Panel B reports the distribution of the number of analysts per firm and the number of firms covered per analyst. I compare the distribution between bond analysts and equity analysts. The number of bond analysts per firm is measured in the individual basis while the number of firms covered by each bond analyst is measured in the team basis. The bond analyst coverage is measured based on the provision of bond analysts' debt reports because many bond analysts do not necessarily issue forecasts on cash flows or earnings, whereas the equity analyst coverage is calculated based on the issuance of earnings forecasts since most equity analysts issue earnings forecasts. Each firm appears to be followed by equity analysts approximately 8 (median comparison) to 10 (mean comparison) times more than by bond analysts. Also, the mean (median) number of firms that each bond analyst covers in a fiscal year is 6 (10) while it is 11 (32) for each equity analyst. This suggests that equity analysts are substantially more active covering and analyzing a firm, which is not surprising given the prior finding that bond market is less liquid.

[31] Since this study provides, for the first time, evidence on bond analysts' forecasts, I provide detailed descriptive information regarding the distribution of bond analysts and their forecasts in Table 3.

[32] Later in this paper, I find that bond analysts are more accurate in forecasting cash flows than equity analysts. One may argue that this superior forecasting ability is primarily driven by the fact that many bond analysts forecast cash flows and earnings as a team. However, Brown and Hugon (2009) document evidence that team forecasters do not necessarily outperform individual forecasters.

Panel C of Table 3 contains frequencies of bond analysts' forecast items and the percentage of each item out of total forecasts and total debt reports. Of total forecasts, bond analysts are more likely to provide forecasts for EBITDA (98.45%), free cash flows (76.29%), or operating cash flows (20.32%) than for earnings (15.92%), whereas equity analysts usually provide forecasts for earnings than for EBITDA and free cash flows. Similarly, of total debt reports bond analysts provide forecasts more frequently for EBITDA (35.68%) and/or free cash flows (27.65%), or operating cash flows (7.36%) than for earnings (5.77%). This suggests that bond analysts are more likely to provide the information on future cash flows from operations that can be used to support debt payment than the information about future earnings. Although not reported, unlike equity analysts bond analysts also issue forecasts on interest coverage and leverage. Finally, more than half of the forecasts (59.51%) have a horizon of shorter than a year (Panel D), which indicates that bond investors have shorter-term perspectives than equity investors.[33]

5. Results

5.1. Results on the propensity to issue cash flow and earnings forecasts between bond analyst and equity analysts.

Since the firms covered by bond and equity analysts in the sample could be inherently different, it is possible that any (unobservable) firm characteristics drive the difference in the probability to issue forecast. Considering this, I construct two different samples to test H1a and H1b. The first sample consists of firm-year observations where both bond analysts and equity analysts issue at least one cash flow or earnings forecast for the same firm and same year: the "Exact Matching" sample. The second sample augments the first sample by adding matched-pair

[33] Unlike equity analysts who emphasize the 'long-term' growth as well as short-term earnings, many bond analysts do not discuss 'long-term' growth in their reports.

observations which are obtained using a propensity-score matching method: the "PS Matching" sample. To the additional matched-pair observations, firm-year observations where bond analysts issued at least one cash flow or earnings forecast but any equity analyst do not cover the firm year are matched with the matched counterparts, which are selected among firm-year observations where equity analysts issued at least one cash flow or earnings forecast but any bond analyst do not cover the firm year, by ensuring that the propensity of bond analysts and equity analysts to issue the forecast is closest. Specifically, I estimate the following probit model:

$$Prob\ (BondDummy{=}1)_{it} = G\ (\theta_0 + \theta_1 SIZE_{it-1} + \theta_2 MB_{it-1} + \theta_3 LEV_{it-1} + \theta_4 INTCOV_{it-1} + \theta_5 DSIZE_{it-1} + \varepsilon_{it}) \quad (7)$$

A binary dependent variable, *BondDummy*, equals one if a cash flow (earnings) forecast is issued by bond analysts, and zero if not (i.e., issued by equity analysts). The explanatory variables, *SIZE*, *MB*, *LEV*, *INTCOV*, and *DSIZE* are included following the determinant model in Johnston et al. (2009). All coefficients are statistically significant and of the hypothesized sign as in Johnston et al. (2009). Based on these estimates, I employ a "nearest neighbor" matching procedure without replacement such that each of bond observation is matched with an equity observation having the closest propensity score for *BondDummy*. Since I match on the propensity score only, the "matched" pairs can be from different years and industries.

Table 4 reports the univariate analysis on the difference between bond and equity analysts in the probability of issuing cash flow and earnings forecasts. Panels A and B show the frequency difference in forecasting cash flows for the exact matching sample and for the PS matching sample, respectively, whereas Panel C and D separately show the frequency difference in forecasting earnings for the two samples. There are 946 (997) firm-year observations where both bond and equity analysts provided at least one annual cash flow (earnings) forecast.[34] The propensity score matching procedure generated additional 179 (192) matched-pair firm-year observations.

The results in panels A and B reveal that bond analysts are more likely to provide cash flow forecasts than equity analysts. Panel A indicates that 80.4% (= 761/946) of bond analysts provide cash flow forecasts whereas only 73.8% (= 699/946) of equity analysts provide earnings forecasts for the exact sample. Panel B also shows that 80.5% (= 906/1,125) of bond analysts provide cash flow forecasts while 32.0% (= 791/1,125) of equity analysts do so for the PS matched sample. Further, panel A shows that the frequency (n = 185) where bond analysts issue cash flow forecasts and equity analysts do not is higher than the frequency (n = 123) where equity analysts issue cash flow forecasts and bond analysts do not (McNemar test statistics = 12.48, p-value < 0.001). Similarly, panel B also indicates bond analysts issue cash flow forecasts absent equity analysts' cash flow forecasts (n = 251) more often than equity analysts issue cash flow forecasts absent bond analysts' cash flow forecasts (n = 136). However, for earnings forecasts the results are quite the opposite. Almost all equity analysts provide earnings forecasts whereas only 32.5% (= 324/997) of bond analysts provide earnings forecasts for the exact sample as shown in panel C and 32.0% (= 381/1,189) for the PS matched sample as seen in panel D. The off-diagonal frequency differences are statistically significant in both panels C and D.

The logistic regression results are reported in Table 5. The variable of my interest is *BondDummy*. A positive coefficient on *BondDummy* where the dependent variable is *CF1_F* indicates that bond analysts, relative to equity analysts, are more likely to provide cash flow forecasts. On the other hand, a negative coefficient on *BondDummy* where the dependent

[34] The slight difference in sample size is due to the restriction that the cash flow (earnings) forecast analysis requires no missing values of control variables such as *CFOVOL* and *CFO* (*EARNVOL* and *EARN*).

variable is *EARN_F* suggests that equity analysts, relative to bond analysts, are more likely to provide earnings forecasts. For both cases, I estimate the models alternately with and without control variables and present the results separately in order to provide some assurance that multicollinearity is not driving the overall results. In column (1) – (4), *BondDummy* is all positive and statistically significant at the 1% level. For example, column (2) shows that the coefficient on *BondDummy* is 0.443 (t-statistic = 2.65), which is supportive of H1a. In contrast, *BondDumm*y is negatively associated with *EARN_F* (e.g., coefficient = -8,073, t-stat = -7.83 in column (6)), consistent with H1b. In sum, both table 4 and 5 provide strong evidence that the relative importance of cash flow (earnings) information is greater (smaller) for bond analysts than for equity analysts.

5.2. Comparison results for forecast bias and accuracy between bond and equity analysts

5.2.1. Univairate Analysis

Similar to the analysis in section 5.1., I first identify observations where both bond and equity analysts issue at least one forecast for the same firm and same year ("Exact Matching"). Then I augment the sample by including additional matched-pair observations using propensity scores ("PS Matching") for firm-year observations where bond analysts issued annual cash flow or earnings forecasts but are not exactly matched with equity analyst sample.[35] Using a binary dependent variable that equals one if a cash flow (or earnings) forecast is issued, and zero if not, I estimate the following probit models:

$$\begin{aligned} Prob\,(CFO\_F=1)_{it} = G\,(&\lambda_0 + \lambda_1 SIZE_{it-1} + \lambda_2 MB_{it-1} + \lambda_3 LEV_{it-1} + \lambda_4 INTCOV_{it-1} \\ &+ \lambda_5 DSIZE_{it-1} + \lambda_6 HORIZON_{it-1} + \lambda_7 CFOVOL_{it-1} + \varepsilon_{it}) \end{aligned} \tag{8-1}$$

[35] The number of exactly matched firm-year observations for CFO, EBITDA, and EARN is 146, 163, and 248, respectively. The number of firm-year observations included by propensity score matching procedure for CFO, EBITDA, and EARN is 65, 590, and 13, respectively.

$$Prob\,(EBITDA\_F{=}1)_{it} = G\,(\lambda'_0 + \lambda'_1 SIZE_{it-1} + \lambda'_2 MB_{it-1} + \lambda'_3 LEV_{it-1} + \lambda'_4 INTCOV_{it-1} + \lambda'_5 DSIZE_{it-1} + \lambda'_6 HORIZON_{it-1} + \lambda'_7 EBITDAVOL_{it-1} + \varepsilon'_{it}) \tag{8-2}$$

$$Prob\,(EARN\_F{=}1)_{it} = G\,(\lambda''_0 + \lambda''_1 SIZE_{it-1} + \lambda''_2 MB_{it-1} + \lambda''_3 LEV_{it-1} + \lambda''_4 INTCOV_{it-1} + \lambda''_5 DSIZE_{it-1} + \lambda''_6 HORIZON_{it-1} + \lambda''_7 EARNVOL_{it-1} + \varepsilon''_{it}) \tag{8-3}$$

SIZE, *MB*, *LEV*, *INTCOV*, and *DSIZE* are included and defined as the same way in model (7). I augment the model by including *HORIZON* and *CFOVOL* (*EBITDAVOL* or *EARNVOL*) because my focus is on the comparison of the forecast quality between bond and equity analysts.

Table 6 reports the univariate analysis on the difference in forecast bias and error between bond and equity analysts.[36] Panels A, B, and C show the mean difference in forecasting bias and accuracy for *CFO*, *EBITDA*, and *EARN*, respectively.[37] In each panel, I compare the mean difference between bond and equity analysts, separately, for the full and the matched samples. The results in panels A and B reveal that bond analysts are providing cash flow forecasts in a more conservative manner than equity analysts. Specifically, panel A shows that the mean difference in *CFO* bias is 0.298 (t-statistic = 4.14) for the full sample and 0.588 (t-statistic = 2.71) for the matched sample. Similarly, panel B indicates that the mean difference in *EBITDA* bias is 0.187 (t-statistic = 9.75) for the full sample and 0.225 (t-statistic = 10.58) for the matched sample. Panel C presents comparison results of forecast bias in earnings between bond and equity analysts. The results in both full and matched samples show that bond analysts' earnings forecasts are also less optimistic than equity analysts' forecasts (mean difference =

[36] Note that in Table 6, accuracy is not multiplied by -1, thus a greater value of error implies lower quality of forecast accuracy.
[37] Using Wilcoxon rank sum test produces qualitatively similar (untabulated) results. In addition, χ^2 test also confirms that the frequency where bond analysts are 1) more conservative or 2) more (less) accurate forecasting cash flows (earnings) than equity analysts is greater than the frequency for the opposite case.

0.225 or 0.337). Overall, *CFO*, *EBITDA*, and *EARN* forecasts are less optimistic for bond analysts than for equity analysts, which supports H2.

Next, consistent with H3, panels A and B of Table 6 indicate that bond analysts are more accurate forecasting *CFO* and *EBITDA* than equity analysts. For example, panel A show that the mean difference in *CFO* forecast error between bond and equity analysts is 0.191 (t-statistic = 2.87) in the full sample and 0.753 (t-statistic = 3.12) in the matched sample. As a supplementary test, I compare the *CFO* forecast error between analyst forecasts and forecast based on a time-series model, which was proposed by Barth, Cram, and Nelson (2001) and used by Givoly et al. (2009) and Call et al. (2013).[38] (Untabulated) results document that both bond and equity analyst forecasts are more accurate than forecast based on a time-series CFO model. In the matched sample, *CFO* forecast error of the time-series model is 1.866 (1.629) larger than bond (equity) analysts' *CFO* forecast accuracy and the difference is statistically significant at 1% level. More importantly, the difference-in-difference average error between bond and equity analysts, is 0.237 (=1.866 – 1.629), implying that bond analysts are more accurate than equity analysts with respect to forecasting *CFO*. Finally, panel C presents comparison results of forecast error in earnings between bond and equity analysts. The results in both full and matched samples show that bond analysts' earnings forecasts are less accurate than equity analysts' forecasts (mean error difference = -1.279 or -0.883), which is supportive of H3.

I plot the intra-year change in both forecast bias and error for bond and equity analysts in Figure 1. For each firm-year, I keep the earliest forecast issued after the previous year's earnings announcement and the last forecast issued before the current year's earnings announcement. All

[38] The predicted operating cash flows are estimated from the following time-series model: $CFO_{it} = \lambda_1 + \lambda_2 CFO_{it-1} + \lambda_3 \Delta AR_{it-1} + \lambda_4 \Delta INV_{it-1} + \lambda_5 \Delta AP_{it-1} + \lambda_6 DEP_{it-1} + \lambda_7 Other_{it-1} + \varepsilon_{it}$. All variables are scaled by average assets. I estimate the model for each industry and year with a requirement of at least 20 observations available. Then I calculate the time-series CFO forecast accuracy with the absolute difference between the predicted operating cash flows and the actual operating cash flows, deflated by the absolute value of actual operating cash flows.

firm-year observations of forecast bias and error are used in this analysis and all firms must have at least two forecasts by both bond and equity analysts within the fiscal period. Panels A, B, and C graph forecast bias and errors of *CFO*, *EBITDA*, and *EAR*N, respectively. There are several observations to note. First, forecast optimism for both bond and equity analysts is lessened throughout the year (Bartov et al., 2002; Cotter et al., 2006; Kross and Suk, 2012), and forecast accuracy improves toward the actual earnings announcement day (Brown, 2001; Kwak et al., 2012). Second, except for the first forecast in earnings, for all three performance measures (i.e., *CFO*, *EBITDA*, and *EARN*) bond analysts exhibit less forecast optimism compared to equity analysts, which is additional evidence supportive of H2. Third, equity analysts are better (worse) earnings (cash flow) forecasters than bond analysts (H3), as shown in panel A, B., and C. In sum, both Table 6 and Figure 1 are generally consistent with H2 and H3.

5.2.2. Multivariate Analysis

I first conduct the regression analysis to examine whether bond analysts are less optimistic (i.e., more conservative) than equity analysts in cash flow and earnings forecasts. Results are reported in Table 7. Note that the sample is based on matched sample as previously described and a negative coefficient on *BondDummy* indicates that bond analyst forecasts are more conservative than equity analyst forecasts. Results in columns (1), (2), and (3) show that bond analysts are more pessimistic than equity analysts in forecasting *CFO* (coefficient = -0.602, t-statistic = -2.36), *EBITDA* (coefficient = -0.149, t-statistic = -4.53), and *EARN* (coefficient = -0.481, t-statistic = -3.20), which supports H2. Turning to the control variables, *HORIZON* is positively associated with forecast optimism, possibly because both analysts' optimism is walked down by the management. As expected, *CFO*, *EBITDA*, and *EARN* are all negatively associated with the forecast bias (i.e, *Bias_CFO, Bias_EBITDA, Bias_EARN)*, respectively, implying that analysts' forecasts becomes less optimistic for lower performance in *CFO*, *EBITDA*, and *EARN*.

Next, the regression results from testing H3 are reported in Table 8. According to H3, bond analysts are predicted to be more (less) accurate in forecasting cash flows (earnings) than equity analysts. Since -1 is multiplied for the forecast accuracy measure, a *larger* (*smaller*) value of the measure indicates forecasts are *more* (*less*) *accurate*. Therefore, *BondDummy* is expected to be positive (negative) when the dependent variable is cash flow (earnings) accuracy. The coefficient on *BondDummy* is positive and significant in the first model (coefficient = 0.844, t-statistic = 3.33) and in the second model (coefficient = 0.152, t-statistic = 4.66), consistent with H3 that bond analysts are better *CFO* and *EBITDA* forecasters than equity analysts. Lastly, the third model shows that bond analysts are less accurate in forecasting earnings than equity analysts, given the coefficient on *BondDummy* is negative and significant (coefficient = -0.925, t-statistic = -5.33), which is consistent with H3. *HORIZON* is also negatively related to accuracy, i.e., as the distance between the forecast date and the actual earnings announcement date is longer, the accuracy of the forecast is lower. *SIZE* is positively associated with forecast accuracy, indicating that larger firms have better informational environments, thus enabling analysts to predict future performance more accurately. In sum, the results in Table 7 and 8 are consistent with H2 and H3, respectively.

5.3. Results on the determinants of bond analysts' cash flow and earnings forecasts provision

The results from estimating the logistic regression (equation (6-1)) is reported in Table 9. I implement two different models: In the first model, *CF1_F* is the dependent variable and *CF2_F* is the dependent variable in the second model. Within each model, I estimate the models alternately with and without control variables (and Inverse Mills Ratio). Consistent with H4a, bond analysts issue cash flow forecasts if there is greater uncertainty in cash flows. The coefficient on *CFOVOL* is positive and statistically significant in all eight specifications, which indicates that the uncertainty in cash flows is an important factor that affects bond analysts' decision on issuing cash flows forecasts. The loading on *CFO* is negative and significant in all specifications, suggesting that bond analysts are more likely to issue cash flows forecasts if the firm is under liquidity constraint. As regards to the control variables, the positive effects of *LEV* on *CF1_F* and *CF2_F* are observed only in columns (1), (3), (5) and (7), where other control variables are omitted. Thus, *LEV* might be statistically insignificant due to multicollinearity in other specifications.[39] *ABSACC* (*ALTMAN*) are positively (negatively) related to *CF1_F* and *CF2_F*. In sum, the results are supportive of my hypothesis that bond analysts tend to issue cash flow forecasts to meet bond investors' demand.

Table 10 presents the results from testing the determinants of bond analysts' earnings forecast provision. All observations must have at least one cash flow forecast, since my interest is to examine why bond analysts issue an earnings forecast *conditional on the issuance of a cash flow forecast*. As discussed in section 3.4., I use two samples: one when *CF1_F*=1 and the other when *CF2_F*=1. As H4b predicts that bond analysts are more likely to provide earnings forecasts when the volatility of accruals is high, the results indicate that the coefficient on *ACCVOL* is positive and statistically significant in all eight columns. Specifically, the coefficient on *ACCVOL* ranges from 5.14 to 5.95 with Z-statistic = 2.25 to 2.50 when the sample is based on *CF1_F* (i.e., when *CF1_F* = 1). The level of earnings (*EARN*) is negatively associated with the probability of issuing earnings forecast (*EARN_F)* in all eight models, suggesting that conditional on cash flow forecast provision, bond analysts are more likely to provide an earnings

[39] The Pearson correlation between *LEV* and *ALTMAN* (*SIZE*) is -0.55 (-0.42).

forecast when the earnings are lower, which supports H4b. Overall, the results in Table 9 and 10 support both H4a and H4b.

5.4. Sensitivity Analysis

5.4.1. Alternative definition of Earnings before Interest, Tax, and Depreciation and Amortization (EBITDA)

In this paper, I define cash flows in a broader way which includes EBITDA as well as CFO and FCF for reasons explained in section 3.2. However, one may argue that EBITDA might be conceptually closer to earnings rather than cash flows. In order to lessen any potential concern that EBITDA does not proxy for cash flows, I identify cases where bond analysts' definition of EBITDA involves explicit adjustment of working capitals to earnings based on full-text bond reports. More specifically, if EBITDA adds not only depreciation and amortization but also adjusts 'working capital', 'deferred items', 'non-cash items', 'non-recurring items' or 'other items' to operating income (or EBIT), then I consider it closer to the definition of cash flows rather than earnings. Out of 3,803 bond reports which include bond analysts' forecasts of EBITDA, 1,902 (50.0%) of EBITDA forecasts by bond analysts are considered cash flows based on this alternative definition EBITDA. I leave only these observations and repeat the analyses in table 6 – 8 for EBITDA.

Table 11 reports the univariate and regression results for both forecast bias and accuracy tests using the alternative definition of EBITDA. Panel A shows that the mean difference in EBITDA forecast bias between bond and equity analysts is 0.200 (t-statistic = 10.43) in the full sample and 0.363 (t-statistic = 3.94) in the matched sample. Similarly, the mean difference in forecast accuracy between bond and equity analysts is 0.260 (t-statistic = 12.28) in the full sample and 0.461 (t-statistic = 4.33) in the matched sample. More importantly, *BondDummy* is still negatively associated with *Bias_EBITDA* (t-statistic = -3.61) and positively associated with

Accu_EBITDA (t-statistic = 3.79) in panel B. Therefore, my main empirical findings that bond analysts are less optimistic in forecasting cash flows than equity analysts and that bond analysts are more accurate forecasting cash flows than equity analysts are insensitive to more rigorous definition of EBITDA.

5.4.2. Influential outliers, alternative forecast consensus, alternative deflator of forecast variables, and alternative values of cash flows and earnings

In this section, I conduct various robustness checks and their results are reported in Table 12. For brevity, I only focus on the robustness on the main variable, *BondDummy*, although control variables are included (but not reported) in the regression model. First, recall that I winsorized all continuous variables at the top and bottom 1% level in my main tests. To mitigate the concern that my results are driven by influential outliers, I truncate all continuous variables at the top and bottom 1% level and repeat the tests in Table 7 and 8. The coefficients on *BondDummy* are still consistent with my predictions all at the 5% significance level. Untabulated results show that dropping observations 1) where the absolute studentized residual is larger than 2 and 2) where the Cook's D is greater than (4/N) do not alter my main inferences.

Second, instead of using the median forecast as the consensus, I use the last forecast issued by each bond or equity analyst as the forecast consensus for each firm-year (O'Brien, 1990). The coefficients on *BondDummy* are still consistent with my predictions all at the 5% significance level. Additionally, when I use the mean forecast value as the consensus, the results are qualitatively similar. For example, *BondDummy* is negatively related to *Bias_CFO* (coefficient = -0.675, t-statistic = -2.41), *Bias_EBITDA* (coefficient = -0.178, t-statistic = -4.81), and *Bias_EARN* (coefficient = -0.550, t-statistic = -3.53). The associations between *BondDummy* and each of *Accu_CFO* (t-statistic = 3.31), *Accu_EBITDA* (t-statistic = 4.99), and *Accu_EARN* (t-statistic = -4,88) are also robust to using mean consensus forecasts.

Third, following prior literature (Givoly et al., 2009), I also deflate forecast bias and accuracy by previous year's stock price rather than actual value as a sensitivity check. The results are generally consistent with my predictions except for the cases where the dependent variable is *Bias_EARN* or *Accu_CFO*, although the sign is as expected. I also deflated by current year's stock price and get similar results.

Finally, many actual values in bond reports are missing. To obtain a larger sample size at the cost of increasing measurement error, I repeat the analyses by retrieving the actual values from Compustat if CFO, EBITDA, or EARN is missing in both bond reports and I/B/E/S. More specifically, net cash flows from operating activities (OANCF), operating income before depreciation (OIBDP), or income before extraordinary items (IB) in Compustat-Annual File are used, for CFO, EBITDA, or EARN, respectively. Panel A and B in table 12 indicates that the results are robust to alternative definition of actual values for bond analysts, expect for the first column in panel A. When I use only the actual values from bond reports, as expected, the sample size decreases from 422 to 212 (CFO), from 1,506 to 1,108 (EBITDA), and from 522 to 214 (EARN). In this case, except for the second first and third columns in Panel A, all the coefficients on *BondDummy* are significant at the 5% level.

6. Concluding Remarks

Using bond analysts' forecast data, this study examines the determinants and properties of their forecasts, in comparison with equity analysts. I first document that the probability to issue cash flow (earnings) forecasts is greater (smaller) for bond analysts than for equity analysts. I also find that bond analysts have conservative view on future firm performance in order to meet bondholders' asymmetric demand on good news and bad news. In addition, although bond analysts' earnings forecast accuracy is lower than that of equity analysts, bond analysts' cash flow forecasts are more accurate than equity analysts. Finally, bond analysts are more likely to provide a forecast on future cash flows when the uncertainty and the constraint of cash flows are greater, and bond analysts' decision to provide earnings forecasts, along with cash flow forecasts, is associated with firm's uncertainty of accruals and earnings performance.

This study contributes to the recent growing literature on the informational role of bond analysts. To the best of my knowledge, this study is the first to document debt analysts' efforts on forecasting firms' future earnings and cash flows. This paper also adds to the literature on other information intermediaries, such as stock analysts. In particular, considering the debate on the quality of analysts' cash flow forecasts, this study shows that equity analysts are inferior to bond analysts with respect to cash flow forecast accuracy. In conclusion, this study elevates our understanding of the informational role bond analysts play in the bond market through their forecasting activities, which are different in various aspects from the role of equity analysts. Future research is encouraged to examine the interaction between equity and bond analysts in forecasting earnings and/or cash flows.

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Appendix A: Variables Description

Variable	Definition
ABSACC	The absolute value of earnings minus operating cash flows divided by average total assets. Earnings are Income before extraordinary items.
Accuracy	(-1) × $\|F_{it} - A_{it}\| / \|A_{it}\|$, where A_{it} = actual value per share for firm i and year t, and F_{it} = (consensus) forecasted values per share for firm i and year t.
Accu_CFOF	Accuracy where the actual and forecasted values are for operating cash flows.
Accu_EBITDAF	Accuracy where the actual and forecasted values are for earnings before interest, tax, and depreciation and amortization.
Accu_EARNF	Accuracy where the actual and forecasted values are for earnings before extraordinary items.
ACCVOL	The firm-specific standard deviation of the total accruals divided by average assets. Total accruals are calculated as the difference between net income before extraordinary items and operating cash flows. Previous seven historical years are used to calculate the standard deviation with the minimum requirement of three years.
ALTMAN	1.2 (Net working capital / Total Assets) + 1.4 (Retained earnings / Total Assets) + 3.3 (Earnings before interest and taxes / Total Assets) + 0.6 (Market value of equity / Book value of liabilities) + 1.0 (Sales / Total Assets).
Bias	$(F_{it} - A_{it}) / \|A_{it}\|$, where A_{it} = actual value per share for firm i and year t, and F_{it} = (consensus) forecasted values per share for firm i and year t.
Bias_CFOF	Bias where the actual and forecasted values are for operating cash flows.
Bias_EBITDAF	Bias where the actual and forecasted values are for earnings before interest, tax, and depreciation and amortization (EBITDA).
Bias_EARNF	Bias where the actual and forecasted values are for earnings before extraordinary items.
BondDummy	An indicator variable which equals to one if the forecast is issued by bond analyst, otherwise (i.e. if the forecast is issued by equity analyst).
BM	Equity book value divided by equity market value.
CAPINT	Gross property, plant, and equipment (Gross PP&E) divided by total sales in the previous year.
CFO	Operating cash flows divided by average total assets.

Appendix A (cont'd)

CF1_F	An indicator variable that equals one if (bond) analysts provide a forecast either on operating cash flows or on free cash flows, and zero otherwise.
CF2_F	An indicator variable that equals one if bond analysts provide any forecast on operating cash flows, free cash flows, or earnings before interest, tax, and depreciation and amortization, and zero otherwise.
CFO_F	An indicator variable that equals one if analysts provide a forecast on operating cash flows, zero otherwise.
CFOVOL	The firm-specific standard deviation of the operating cash flows divided by average assets. Previous seven years are used to calculate the standard deviation with the minimum requirement of three years.
DSIZE	The natural logarithm of book value of debt.
EARN	Income before extraordinary items divided by average total assets.
EARN_F	An indicator variable which equals one if (bond) analysts forecast earnings, zero otherwise.
EARNVOL	The firm-specific standard deviation of earnings divided by average assets. Previous seven years are used to calculate the standard deviation with the minimum requirement of three years.
EBITDA	Earnings before depreciation and amortization divided by average assets.
EBITDA_F	An indicator variable which equals one if analyst forecast EBITDA, zero otherwise.
EBITDAVOL	The firm-specific standard deviation of earnings before depreciation and amortization divided by average assets. Previous seven years are used to calculate the standard deviation with the minimum requirement of three years.
HORIZON	The difference (in days) between the earnings announcement date and the forecast issuance date.
INTCOV	Operating income divided by interest payments.
LEV	The book value of debt divided by book value of equity.
LOSS	Dummy variable which equals one if *EARN* is negative, zero otherwise.
MB	Equity market value divided by equity book value.
SIZE	The natural logarithm of the equity market capitalization, which equals the number of shares outstanding times the end of year price.

Appendix B. Sample reports of debt and equity analysts' cash flow and earnings forecasts
1. *Bond* analyst report [excerpted from Deutsche Bank (2008) covering RSC Holdings Inc.]

25 April 2008

RSC

Reports In-line Q1 08 Results; Maintain BUY

Results Review

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Investment Opinion – Maintain BUY on 9.5% Senior Notes

($ in millions)	Dec-04 A	Dec-05 A	Dec-06 A	Dec-07A	Dec-08E
Revenue	1,329	1,461	1,654	1,769	1,798
Adjusted EBITDA	449	568	726	825	796
Operating Income	223	322	432	477	430
Earnings Before Taxes	148	176	214	223	207
Net Income	92	111	127	144	124
Pro-forma Cash Flow					
Net Income	92	122	137	124	123
Depreciation and Amortization	226	246	292	342	362
Working Capital	71	95	(73)	30	(163)
Other	18	27	87	9	(40)
Cash From Operations	407	490	443	505	282
Gross Capital Expenditures	(453)	(697)	(750)	(601)	(350)
Proceeds From Equipment Sale	181	218	192	145	122
Free Cash Flow	135	11	(115)	49	54

2. *Equity* analyst report [excerpted from Deutsche Bank (2008) covering RSC Holdings Inc.]

25 April 2008

RSC

Reuters: **RRR.N** Bloomberg: **RRR UN** Exchange: **NYS** Ticker: **RRR**

Seasonally Soft 1Q, Maintain Ests on Positive Outlook

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Modest EPS miss on lower sales & 1Q seasonality

Results Review

Buy

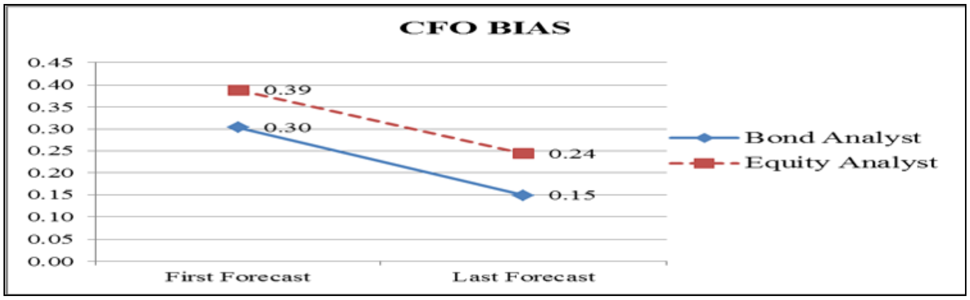
Price at 24 Apr 2008 (USD)	10.84
Price target	20.00
52-week range	22.23 - 9.81

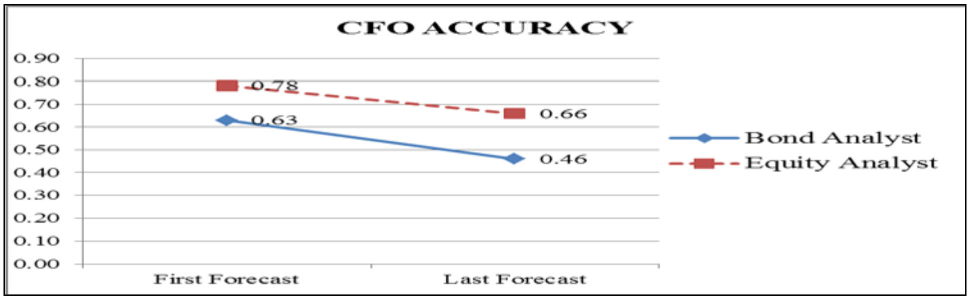
Key changes		
EPS (USD)	1.56 to 1.54 ↓	-0.9%
Revenue (USDm)	1,833.8 to 1,826.3 ↓	-0.4%

Fiscal year end 31-Dec	2005	2006	2007	2008E
Income Statement (USDm)				
Sales	1,461	1,653	1,769	1,826
EBITDA	571	725	824	850
EBIT	325	433	482	482
Pre-tax profit	261	317	239	267
Net income	167	199	147	160
Cash Flow (USDm)				
Cash flow from operations	559	436	505	396
Net Capex	-463	-542	-444	-218
Free cash flow	96	-106	61	178

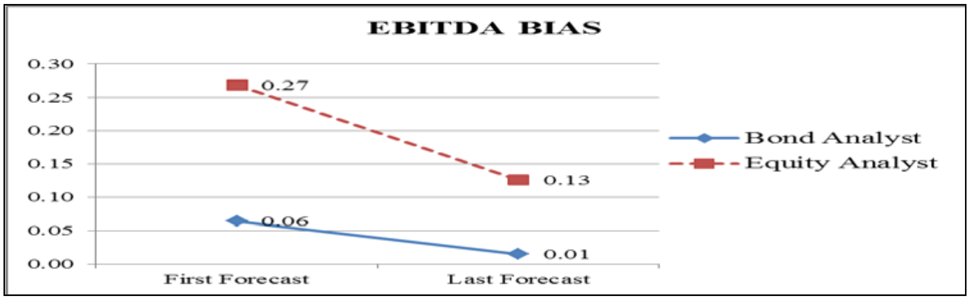
Figure 1. Intra-year Change in Forecast Bias and Forecast Accuracy between Bond Analysts and Equity Analysts

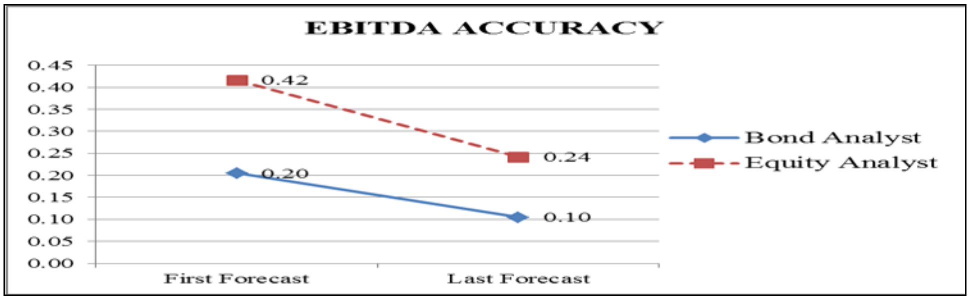
Panel A. Forecast Item – Operating Cash Flows (CFO)



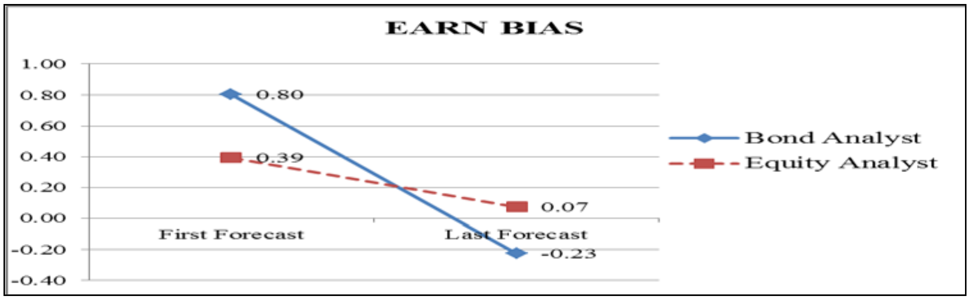


Panel B. Forecast Item – Earnings before Interest, Tax, and Depreciation and Amortization (EBITDA)





Panel C. Forecast Item – Earnings (EARN)



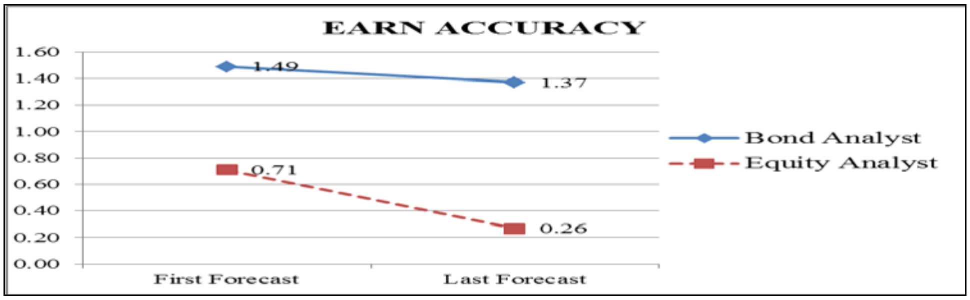


Figure 1 plots the intra-year improvement of forecast bias and accuracy for both bond and equity analysts. Panel A, B, and C graphs the forecast bias and accuracy of *CFO*, *EBITDA*, and *EARN*, respectively. All firms must have at least two forecasts by both bond and equity analysts within the fiscal period. For each firm and year, I keep the earliest forecast issued after previous year's earnings announcement and the last forecast issued before the current earnings announcement. All observations that are able to calculate the bias and accuracy are used in this analysis. $Bias_{it} = (F_{it} – A_{it}) / |A_{it}|$, where A_{it} = actual value per share for firm i and year t, and F_{it} = forecasted value per share for firm i and year t. $Accuracy_{it} = |F_{it} - A_{it}| / |A_{it}|$. All variables are winsorized at the top and bottom 1%.

Table 1. Sample Construction

	Number of bond analyst reports	*Number of firm-year observations*	*Number of unique firms*
Initial Reports from Investext: 2001 - 2010	12,478	4,396	1,847
1. *Less*: Reports issued 1) for non-US firms 2) for close-end fund, convertible bond, or derivative 3) within two days by the same analyst (i.e. duplicate report) 4) for multiple firms within a single report 5) at macro or industry level 6) by equity analysts 7) simultaneously by equity analysts 8) by credit rating agencies (e.g., Fitch, Rapid)	(1,818)	(808)	(623)
Bond Reports before Merging with Compustat	**10,660**	**3,588**	**1,224**
2-1. *Less*: Missing Compustat data		(2,642)	(832)
Cash Flow Forecast Determinant Test (H1a)		**946**	**392**

This table presents the sample selection process. I obtain all bond reports from *Investext*, a provider of full-text bond analysts' reports between 2001 and 2010. The initial bond reports were downloaded using the following three search criteria: 1) asset class must be fixed income, 2) reports must be issued within the "North America" region, and 3) industrial-, geographic-, or macroeconomic-level research reports are excluded.

Table 2. Descriptive Statistics on Firm Characteristics
Panel A: Distribution by Year

Fiscal year	*Number of bond reports*		*Number of firms with bond reports*		*Number of annual forecasts*		*Number of quarterly forecasts*	
	Frequency	*Percent*	*Frequency*	*Percent*	*Frequency*	*Percent*	*Frequency*	*Percent*
2001	415	3.89%	227	6.31%	93	2.41%	60	2.52%
2002	1,157	10.85%	409	11.38%	405	10.48%	179	7.53%
2003	1,831	17.18%	543	15.10%	662	17.14%	358	15.05%
2004	2,327	21.83%	621	17.27%	875	22.65%	639	26.87%
2005	1,222	11.46%	471	13.10%	423	10.95%	256	10.77%
2006	540	5.07%	252	7.01%	199	5.15%	144	6.06%
2007	755	7.08%	279	7.76%	297	7.69%	171	7.19%
2008	1,234	11.58%	382	10.63%	457	11.83%	308	12.95%
2009	614	5.76%	240	6.68%	244	6.32%	133	5.59%
2010	565	5.30%	171	4.76%	208	5.38%	130	5.47%
Total	10,660	100.00%	3,595	100.00%	3,863	100.00%	2,378	100.00%

Table 2. Descriptive Statistics on Firm Characteristics (Continued)
Panel B: Firm Characteristics (Full Sample)

Variables	*# of Obs. (BA)*	*# of Obs. (EA)*	*Mean (BA)*	*Mean (EA)*	*Diff. (BA - EA)*	*P-value*[1]	*Median (BA)*	*Median (EA)*	*Diff. (BA - EA)*	*P-value*[2]
MV ($ billion)	2,180	28,148	10.61	5.50	**5.11**	**<.0001**	2.72	0.72	**2.00**	**<.0001**
ROA	2,180	28,148	0.01	-0.02	**0.03**	**<.0001**	0.02	0.04	**-0.01**	**<.0001**
LOSS	2,180	28,148	0.31	0.30	0.00	0.6894	0.00	0.00	0.00	0.6894
MB	2,180	28,148	3.87	4.20	-0.32	0.6890	1.71	2.03	**-0.32**	**<.0001**
LEV	2,180	28,148	0.65	0.35	**0.30**	**<.0001**	0.57	0.31	**0.26**	**<.0001**
INTCOV	2,180	28,148	3.99	64.98	**-60.98**	**<.0001**	2.37	4.38	**-2.01**	**<.0001**
DSIZE	2,180	28,148	8.21	5.94	**2.27**	**<.0001**	8.21	5.93	**2.28**	**<.0001**
ALTMAN	2,180	28,148	1.96	3.64	**-1.68**	**<.0001**	1.68	2.89	**-1.21**	**<.0001**
VOLEARN	2,180	28,148	0.05	0.12	**-0.07**	**<.0001**	0.03	0.05	**-0.02**	**<.0001**
VOLACC	2,180	28,148	0.05	0.10	**-0.05**	**<.0001**	0.03	0.05	**-0.02**	**<.0001**
VOLCFO	2,180	28,148	0.04	0.09	**-0.05**	**<.0001**	0.03	0.05	**-0.02**	**<.0001**

Panel C: Firm Characteristics (PS Matched Sample)

Variables	*# of Obs. (BA)*	*# of Obs. (EA)*	*Mean (BA)*	*Mean (EA)*	*Diff. (BA - EA)*	*P-value*[1]	*Median (BA)*	*Median (EA)*	*Diff. (BA - EA)*	*P-value*[2]
MV ($ billion)	1,125	1,125	6.87	5.74	1.13	0.5136	1.41	1.41	0.00	0.8801
ROA	1,125	1,125	0.00	0.00	0.00	0.6734	0.01	0.01	0.00	0.2675
LOSS	1,125	1,125	0.40	0.38	0.02	0.2808	0.00	0.00	0.00	0.2807
MB	1,125	1,125	2.38	2.33	0.04	0.7666	1.57	1.57	0.01	0.9217
LEV	1,125	1,125	0.66	0.64	0.02	0.1135	0.62	0.61	0.01	0.1507
INTCOV	1,125	1,125	2.34	2.50	-0.16	0.2224	1.82	1.94	-0.13	0.1328
DSIZE	1,125	1,125	7.81	7.83	-0.02	0.7698	7.78	7.77	0.01	0.8418
ALTMAN	1,125	1,125	1.63	1.64	-0.01	0.8329	1.54	1.56	-0.02	0.7547
VOLEARN	1,125	1,125	0.06	0.06	-0.01	0.3525	0.04	0.04	0.00	0.7355
VOLACC	1,125	1,125	0.06	0.06	-0.01	0.3427	0.04	0.04	0.00	0.9987
VOLCFO	1,125	1,125	0.04	0.05	0.00	0.4430	0.04	0.04	0.00	0.9926

This table reports descriptive statistics on the firms covered by bond analysts and equity analysts. Panel A tabulates the annual distribution of the number of bond reports, the number of firms with bond reports, the number of annual bond analysts' forecasts, and the number of quarterly bond analysts' forecasts. The sample is based on 10,660 bond reports before matching with Compustat file. Panel B compares the industrial distribution between firms covered by bond analysts and equity analysts. The industry definition is based on the Fama and French (1997) 48-industry classification. Industries with less than 2% of the overall sample are combined and reported as "others." Both samples are constructed from the intersection of *Investext*, *I/B/E/S*, and *Compustat*. The number of observation is at the (unique) firm-level. Panel C and D compare the difference in characteristics between firms covered by bond analysts and firms covered by equity analysts. In panel C, all firm-year observations available between 2001 and 2010 are used. In panel D, firm-year observations are based on the sample used for testing H1a. First, firm-year observations where both bond and equity analysts issue at least one forecast for the same firm and same year are identified and used. Second, firms with bond analysts' forecasts are matched with firms covered by equity analysts using the propensity matching technique. *SIZE*, *MB*, *LEV*, *INTCOV*, and *DSIZE* are used to identify the closest match. If the mean (median) difference is statistically significant at the 10% level, then the mean (median) difference and the p-value are in bold. The first p-value is based on t-statistics from two-tailed tests, and the second is based on Wilcoxon-Rank Sum tests. Refer to Appendix A for the definitions of variables.

Table 3. Descriptive Statistics on Bond Analysts and Their Forecasts
Panel A: Distribution of Brokerage Firms

Investment Banking	*Number of Bond Reports*	*Percentage*	*Number of Bond Analysts*	*Percentage*
Bear Sterns and Co. Inc	1,256	11.78%	59	10.55%
CIBC World Markets Corp	1,222	11.46%	30	5.37%
CREDIT SUISSE	150	1.41%	31	5.55%
Deutsche Bank	4,137	38.81%	85	15.21%
HSBC	240	2.25%	22	3.94%
JP Morgan	595	5.58%	59	10.55%
Keybanc Capital Markets	486	4.56%	7	1.25%
Morgan Stanley	833	7.81%	104	18.60%
Morgan Keegan & Co	308	2.89%	14	2.50%
RBC Capital Markets	483	4.53%	29	5.19%
UBS	815	7.65%	58	10.38%
*Others**	135	1.27%	61	10.91%
Total	10,660	100.00%	559	100.00%

Panel B: Number of Bond (or Equity) Analysts per Firm and Number of Firms per Bond (or Equity) Analysts.

Number of analysts per firm	*N*	*Mean*	*25%*	*Median*	*75%*
Bond analyst (as an individual)	1,224	4.42	2	3	6
Equity analyst	7,342	47.57	7	24	62

Number of firms per analyst	*N*	*Mean*	*25%*	*Median*	*75%*
Bond analyst (as a team)	517	10.46	1	6	16
Equity analyst	10,793	32.36	3	11	41

Table 3. Descriptive Statistics on Bond Analysts and Their Forecasts (Continued)
Panel C: Distribution of Forecast Items

Forecast item	*Number of forecasts*	*% of forecasts out of total forecasts*	*% of forecasts out of total reports*
EBITDA	3,803	98.45%	35.68%
Free Cash Flows	2,947	76.29%	27.65%
Operating Cash Flows	785	20.32%	7.36%
EBIT	738	19.10%	6.92%
Earnings	615	15.92%	5.77%
Total Forecasts	3,863	100.00%	36.24%
Total Reports	10,660	-	100.00%

Panel D: Forecast Horizon (between the forecast release date and the target fiscal year end date)

Time (in years)	*Number of Forecasts*	*Percent*
Year < 1	2,299	59.51%
1 ≤ Year < 2	1,310	33.91%
2 ≤ Year < 3	195	5.05%
Year ≥ 3	59	1.53%
Total	3,863	100.00%

Panel A tabulates the distributions of brokerage firms employing bond analysts. The sample is based on 10,660 bond reports before matched with Compustat file between 2001 and 2010. *Others include brokerage firms with less than 1% of the sample, such as CITI, ING bank, Societe Generale, or Unicredit Research etc. Panel B presents the distribution of analysts for each firm and the distribution of firms for each analyst. I compare the distribution between bond analysts and equity analysts. The number of bond analysts per firm is measured in the individual basis while the number of firms covered by each bond analyst is measured in the team basis. The definition of bond analyst coverage is based on the debt report provision whereas the definition of equity analyst coverage is based on the earnings forecast provision. Panel C contains frequencies of bond analysts' forecast items and the percentage of each item out of total forecasts and total debt reports. Panel D reports the forecast horizon, the forecast release date relative to the end of targeted fiscal year measured in years. For example, if the target fiscal year end is December 31, 2013 and the forecast release date is September 21, 2012, then the horizon is calculated as 1.25 (year).

Table 4. The Propensity to Issue Cash Flow (Earnings) Forecast between Bond Analyst and Equity Analyst: Univariate Analysis

Panel A. Cash Flow Forecast: Exact Matching

		Bond Analyst		
		1	0	Total
Equity Analyst	1	576	123	699
	0	185	62	247
	Total	761	185	946

McNemar Test Statistic (S) = 12.48*** [p-value = <.0001]

Panel B. Cash Flow Forecast: PS Matching

		Bond Analyst		
		1	0	Total
Equity Analyst	1	655	136	791
	0	251	83	334
	Total	906	219	1,125

McNemar Test Statistic (S) = 34.17*** [p-value = <.0001]

Panel C. Earnings Forecast: Exact Matching

		Bond Analyst		
		1	0	Total
Equity Analyst	1	324	672	996
	0	0	1	1
	Total	324	673	997

McNemar Test Statistic (S) = 672.00*** [p-value = <.0001]

Panel D. Earnings Forecast: PS Matching

		Bond Analyst		
		1	0	Total
Equity Analyst	1	381	805	1,186
	0	0	3	3
	Total	381	808	1,189

McNemar Test Statistic (S) = 805.00*** [p-value = <.0001]

This table presents the 2 × 2 contingency tables tabulating the frequency of issuing cash flow or earnings forecasts by bond analysts and equity analysts. All observations must have at least one annual forecasts by both bond and equity analysts. Panel A and B report the number of cash flow forecast provisions where exact matching procedure is used in panel A and propensity matching procedure is implemented in panel B. Panel C and D report the number of earnings forecast provisions where exact matching procedure is used in panel C and propensity matching procedure is used in panel D. McNemar test statistic is used to determine whether the difference in marginal probabilities is statistically significant.

Table 5. The Propensity to Issue Cash Flow (Earnings) Forecast between Bond Analyst and Equity Analyst: Multivariate Test

Independent Variables	*Predicted Sign*	*Dependent Variable: CF1_F*				*Predicted Sign*	*Dependent Variable: EARN_F*			
		Exact Matching		*PS Matching*			*Exact Matching*		*PS Matching*	
		(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
Intercept		2.295*** (6.18)	-0.963* (-1.70)	0.479 (0.91)	-2.421*** (-3.79)		4.025*** (7.82)	3.291*** (4.65)	2.631*** (2.58)	1.824* (1.67)
BondDummy	(+)	0.417*** (2.68)	0.443*** (2.65)	0.559*** (4.09)	0.597*** (4.03)	(–)	-8.050*** (-7.82)	-8.073*** (-7.83)	-7.485*** (-10.27)	-7.503*** (-10.28)
CFOVOL			0.002 (0.28)		0.006 (0.69)					
CFO			0.723 (0.61)		1.924* (1.77)					
ABSACC			-0.948 (-1.14)		-0.896 (-1.25)					
CAPINT			0.690*** (3.33)		0.480*** (2.68)					
ALTMAN			-0.125* (-1.84)		-0.111* (-1.91)					
ACCVOL								0.007 (0.31)		0.007 (0.35)
EARN								-1.759* (-1.83)		-1.332 (-1.53)
SIZE			0.398*** (7.61)		0.367*** (8.56)			0.102 (1.51)		0.107* (1.88)
Year Fixed Effect		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
N		1,890	1,890	2,250	2,250		1,994	1,994	2378	2378
Pseudo R^2		9.00%	14.20%	10.28%	15.43%		54.37%	54.65%	54.32%	54.57%

Table 5 reports the logistic regression results of H1a and H1b. The regression is implemented for firm-year observations between 2001 and 2010 where all observations must have at least one annual forecast available. All independent variables are winsorized at the top and bottom 1%. Refer to Appendix A for the definitions of variables. Year dummies are included and standard errors are clustered by firm. Z-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, from two-tailed tests.

Table 6. Univariate Analysis of Forecast Bias and Error Comparison between Bond Analysts and Equity Analysts
Panel A: Operating Cash Flows (CFO)

	Full Sample				*Matched Sample*			
	Bias		*Error*		*Bias*		*Error*	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*	*N*	*Mean*
(1) Equity Analyst	15,027	0.283	15,027	0.701	211	0.593	211	1.268
(2) Bond Analyst	215	-0.015	215	0.510	211	0.004	211	0.515
diff.(1) - (2)		0.298		0.191		0.588		0.753
t-statistic		**4.14*****		**2.87*****		**2.71*****		**3.12*****

Panel B: Earnings Before Interest, Taxes, and Depreciation and Amortization (EBITDA)

	Full Sample				*Matched Sample*			
	Bias		*Error*		*Bias*		*Error*	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*	*N*	*Mean*
(1) Equity Analyst	6,507	0.216	6,507	0.362	753	0.143	753	0.272
(2) Bond Analyst	796	0.029	796	0.137	753	0.030	753	0.140
diff.(1) - (2)		0.187		0.225		0.112		0.132
t-statistic		**9.75*****		**10.58*****		**4.52*****		**5.41*****

Panel C: Earnings (EARN)

	Full Sample				*Matched Sample*			
	Bias		*Error*		*Bias*		*Error*	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*	*N*	*Mean*
(1) Equity Analyst	49,334	0.096	49,334	0.252	261	0.084	261	0.284
(2) Bond Analyst	267	-0.129	267	1.531	261	-0.254	261	1.166
diff.(1) - (2)		0.225		-1.279		0.337		-0.883
t-statistic		1.27		**-4.91*****		**2.79*****		**-6.60*****

This table presents univariate test results of comparing the average bias and error between bond and equity analysts. All tests are conducted for firm-year observations between 2001 and 2010. Both *Bias* and *Error* are winsorized at the top and bottom 1%. $Bias_{it} = (F_{it} - A_{it}) / |A_{it}|$, where A_{it} = actual value per share for firm i and year t, and F_{it} = median consensus forecasted value per share for firm i and year t. $Error_{it} = |F_{it} - A_{it}| / |A_{it}|$. Panels A, B, and C report the forecast bias and error of *CFO*, *EBITDA*, and *EARN*, respectively, for each of panel full and matched samples. I define the matched sample from the following two steps: First, firm-year observations where both bond and equity analysts issue at least one forecast for the same firm and same year are identified and used. Second, firms with bond analysts' forecasts are matched with firms covered by equity analysts using the propensity matching technique. *SIZE*, *MB*, *LEV*, *INTCOV*, *DSIZE*, *HORIZON*, and *CFOVOL* (*EBITDAVOL* or *EARNVOL*) are used to identify the closest match. If the mean difference is statistically significant at the 10% level from two-tailed tests, then the mean difference and the t-statistics are in bold. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, from two-tailed tests.

Table 7. Regression Results of Forecast Bias Comparison between Bond and Equity Analysts

Independent Variables	*Predicted Sign*	*Dependent Variable: Bias_CFO*		*Dependent Variable: Bias_EBITDA*		*Dependent Variable: Bias_EARN*	
		Coeff.	*t-stat*	*Coeff.*	*t-stat*	*Coeff.*	*t-stat*
Intercept		-0.142	-0.11	0.458***	4.24	-0.298	-0.54
BondDummy	(–)	-0.602**	-2.36	-0.149***	-4.53	-0.481***	-3.20
CFOVOL		-3.212	-0.81				
CFO		-4.237***	-2.73				
EBITDAVOL				0.094	0.37		
EBITDA				-1.180***	-5.94		
EARNVOL						-1.322	-0.94
EARN						-0.431	-0.89
HORIZON		0.003**	2.19	0.0003*	1.71	0.002**	2.00
SIZE		0.021	0.19	-0.036***	-4.24	-0.041	-0.82
BM		0.819*	1.82	0.010	0.32	0.107	0.98
LEV		0.219	0.65	-0.018	-0.36	-0.150	-0.49
Year Fixed Effect		Yes		Yes		Yes	
N		422		1,506		522	
Adj. R^2		6.31%		7.54%		6.20%	

This table presents the regression results for forecast bias comparison between bond and equity analysts. The regression is implemented for firm-year observations where bond analyst sample is matched with equity analyst sample. Refer to table 6 for more detail in the matching procedure. All variables, except for *BondDummy*, are winsorized at the top and bottom 1%. Refer to Appendix A for the definitions of variables. Column (1) contains comparison test results between bond and equity analysts for *CFO*. Column (2) tabulates comparison test results between bond and equity analysts for *EBITDA*. Column (3) reports comparison test results between bond and equity analysts for *EARN*. Year dummies are included, and standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, from two-tailed tests.

Table 8. Regression Results of Forecast Accuracy Comparison between Bond and Equity Analysts

Independent Variables	*Predicted Sign*	*Dependent Variable: Accu_CFO*		*Dependent Variable: Accu_EBITDA*		*Predicted Sign*	*Dependent Variable: Accu_EARN*	
		Coeff.	*t-stat*	*Coeff.*	*t-stat*		*Coeff.*	*t-stat*
Intercept		-1.041	-0.80	-0.351***	-3.42		-1.475**	-2.55
BondDummy	(+)	0.844***	3.33	0.152***	4.66	(–)	-0.925***	-5.33
CFOVOL		-1.698	-0.33					
CFO		8.290***	4.81					
EBITDAVOL				-0.562**	-2.23			
EBITDA				1.383***	6.57			
EARNVOL							-1.733	-1.13
EARN							-0.145	-0.28
HORIZON		-0.003**	-2.33	-0.001***	-4.14		0.001	0.64
SIZE		0.109	0.96	0.027***	3.10		0.120**	2.28
BM		-0.848*	-1.76	0.009	0.26		0.053	0.67
LEV		-0.554	-1.37	-0.020	-0.42		-0.027	-0.08
Year Fixed Effect		Yes		Yes			Yes	
N		422		1,506			522	
Adj. R^2		12.70%		10.20%			11.18%	

This table presents the results of forecast accuracy comparison between bond and equity analysts. The regression is implemented for firm-year observations where bond analyst sample is matched with equity analyst sample. Refer to table 6 for more detail in the matching procedure. All variables, except for *BondDummy*, are winsorized at the top and bottom 1%. Refer to Appendix A for the definitions of variables. Column (1) contains comparison test results between bond and equity analysts for *CFO*. Column (2) tabulates comparison test results between bond and equity analysts for *EBITDA*. Column (3) reports comparison test results between bond and equity analysts for *EARN*. Year dummies are included, and standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, from two-tailed tests.

Table 9. Determinants of Bond Analysts' Issuance of Cash Flow Forecasts

Independent Variables	*Predicted Sign*	*Dependent Variable: CF1_F*				*Dependent Variable: CF2_F*			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept		-1.205	3.231**	-4.366***	14.450***	-1.485	3.926***	-5.356***	17.480***
		(-0.95)	(2.45)	(-3.55)	(2.74)	(-1.13)	(2.94)	(-4.15)	(3.20)
CFOVOL	(+)	10.200***	5.479**	6.848***	5.931**	13.940***	8.318***	9.820***	8.988***
		(4.04)	(2.14)	(2.64)	(2.31)	(4.99)	(2.97)	(3.50)	(3.17)
CFO	(–)	-2.622***	-1.478***	-2.586***	-1.379**	-2.486***	-1.140**	-2.493***	-1.024*
		(-5.41)	(-2.76)	(-5.45)	(-2.54)	(-5.05)	(-2.06)	(-5.28)	(-1.84)
LEV		0.725***	-0.409	1.693***	-2.365**	0.904***	-0.501	2.111***	-2.871***
		(2.79)	(-1.25)	(5.54)	(-2.40)	(3.15)	(-1.39)	(5.87)	(-2.84)
EARNVOL			0.005		0.005		0.001		0.001
			(0.52)		(0.51)		(0.11)		(0.12)
ABSACC			2.200**		2.182*		2.838**		2.822**
			(1.96)		(1.92)		(2.38)		(2.34)
CAPINT			-0.019		-0.027		-0.038		-0.047
			(-0.37)		(-0.51)		(-0.69)		(-0.85)
ALTMAN			-0.217***		-0.220***		-0.240***		-0.237***
			(-2.85)		(-2.82)		(-2.96)		(-2.89)
SIZE			-0.212**		-0.105		-0.297***		-0.175
			(-2.00)		(-0.95)		(-2.65)		(-1.50)
MB			-0.001		0.024		0.007		0.038*
			(-0.07)		(1.10)		(0.42)		(1.69)
DSIZE			-0.204*		-0.964***		-0.212		-1.126***
			(-1.65)		(-2.77)		(-1.63)		(-3.12)
IMR				1.453***	-2.860**			1.774***	-3.454***
				(6.33)	(-2.23)			(7.07)	(-2.59)
Year Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N with (without) cash flow forecasts		755 (1,055)	755 (1,055)	755 (1,055)	755 (1,055)	937 (873)	937 (873)	937 (873)	937 (873)
Total N		1,810	1,810	1,810	1,810	1,810	1,810	1,810	1,810
Pseudo R^2		6.23%	11.97%	9.13%	12.25%	5.86%	14.08%	10.19%	14.47%

This table reports the logistic regression results of why bond analysts issue cash flow forecasts. The regression is implemented for firm-year observations between 2001 and 2010. All independent variables are winsorized at the top and bottom 1%. Refer to Appendix A for the definitions of variables. Year dummies are included and standard errors are clustered by firm. Z-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, from two-tailed tests.

Table 10. Determinants of Bond Analysts' Issuance of Earnings Forecasts together with Cash flow Forecasts

		Dependent Variable: EARN_F							
Independent Variables	*Predicted Sign*	*Sample Based on CF1_F*				*Sample Based on CF2_F*			
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept		-1.412*** (-3.63)	-0.883 (-0.68)	-1.764** (-2.16)	26.930* (1.85)	-1.339*** (-3.65)	-0.321 (-0.28)	-1.769** (-2.47)	34.290** (2.37)
ACCVOL	(+)	5.259** (2.27)	5.316** (2.30)	5.143** (2.25)	5.952** (2.50)	4.380** (2.30)	4.874*** (2.62)	4.146** (2.18)	5.823*** (3.06)
EARN	(–)	-4.795*** (-3.75)	-5.370*** (-3.33)	-5.018*** (-3.77)	-5.231*** (-3.18)	-4.291*** (-3.81)	-4.343*** (-2.90)	-4.584*** (-3.85)	-4.100*** (-2.69)
ALTMAN			0.013 (0.10)		0.014 (0.11)		0.0003 (0.00)		0.010 (0.09)
SIZE			-0.628*** (-3.22)		-0.538*** (-2.62)		-0.697*** (-3.78)		-0.578*** (-2.95)
MB			0.064* (1.71)		0.154*** (2.79)		0.042 (1.20)		0.156*** (2.93)
LEV			-2.732*** (-4.24)		-8.467*** (-2.78)		-2.784*** (-4.87)		-9.997*** (-3.28)
DSIZE			0.711*** (2.83)		-0.985 (-1.06)		0.725*** (3.17)		-1.391 (-1.50)
IMR				0.221 (0.50)	-6.963* (-1.92)			0.272 (0.71)	-8.644** (-2.42)
Year Fixed Effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N with (without) earnings forecasts		114 (641)	114 (641)	114 (641)	114 (641)	132 (805)	132 (805)	132 (805)	132 (805)
Total N		755	755	755	755	937	937	937	937
Pseudo R^2		19.10%	22.87%	19.17%	23.44%	15.41%	19.52%	15.52%	20.26%

This table contains the logistic regression results of why bond analysts issue earnings forecasts. The regression is implemented for firm-year observations between 2001 and 2010, and must have at least one cash flow forecast. All independent variables are winsorized at the top and bottom 1%. Refer to Appendix A for the definitions of variables. Year dummies are included and standard errors are clustered by firm. Z-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, from two-tailed tests.

Table 11. Alternative Definition of Earnings before Interest, Tax, and Depreciation and Amortization (EBITDA)

Panel A: Univariate Analysis

	Full Sample				*Matched Sample*			
	Bias		*Error*		*Bias*		*Error*	
	N	*Mean*	*N*	*Mean*	*N*	*Mean*	*N*	*Mean*
(1) Equity Analyst	6,507	0.216	6,507	0.362	384	0.381	384	0.566
(2) Bond Analyst	413	0.016	413	0.102	384	0.018	384	0.105
diff.(1) - (2)		0.200		0.260		0.363		0.461
t-stat		10.43***		12.28***		3.94***		4.33***

Panel B: Regression Analysis

Independent Variables	*Predicted Sign*	*Dependent Variable: Bias_EBITDA*		*Predicted Sign*	*Dependent Variable: Accu_EBITDA*	
		Coeff.	*t-stat*		*Coeff.*	*t-stat*
Intercept		0.891***	2.77		-0.824**	-2.50
BondDummy	(–)	-0.339***	-3.61	(+)	0.408***	3.79
EBITDAVOL		0.094	0.88		-1.788	-1.26
EBITDA		-1.428**	-2.00		1.766**	2.17
HORIZON		0.001**	2.17		-0.002**	-2.56
SIZE		-0.086***	-2.93		0.074**	2.27
BM		-0.117	-1.19		0.157	1.45
LEV		-0.089	-0.58		0.066	0.39
Year Fixed Effect		Yes			Yes	
N		768			768	
Adj. R^2		5.79%			6.62%	

In table 11, the empirical tests on H2 and H3 using EBITDA is repeated based on alternative definition of EBITDA. More specifically, observations are used only if EBITDA adds not only depreciation and amortization but also adjusts 'working capital', 'deferred items', 'non-cash items', 'non-recurring items', or 'other items'. Panel A presents the univariate test results of comparing the average bias and accuracy between bond and equity analysts. Panel B tabulates the results of forecast bias and accuracy comparison between bond and equity analysts. The regression is implemented for firm-year observations where bond analyst sample is matched with equity analyst sample. Refer to table 6 for more detail in the matching procedure. All variables, except for *BondDummy*, are winsorized at the top and bottom 1%. Refer to Appendix A for the definitions of variables. Column (1) contains bias comparison test result between bond and equity analysts. Column (2) tabulates accuracy comparison test results between bond and equity analysts. Year dummies are included, and standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, from two-tailed tests.

Table 12. Influential Outliers, Alternative Forecast Consensus, Alternative Deflator of Forecast Variables, and Alternative Values of Cash Flows and Earnings

Panel A: Forecast Bias

Independent Variable: BondDummy	*Dependent Variable: Bias_CFO*			*Dependent Variable: Bias_EBITDA*			*Dependent Variable: Bias_EARN*		
	N	*Coeff.*	*t-stat*	*N*	*Coeff.*	*t-stat*	*N*	*Coeff.*	*t-stat*
(1) *Truncation at the top and bottom 1%*	342	-0.734**	-2.42	1,190	-0.101***	-4.04	434	-0.342***	-2.74
(2) *Last forecast as consensus*	422	-0.555**	-2.25	1,506	-0.109***	-3.98	522	-0.460***	-3.11
(3) *Prior year price as deflator*	420	-0.128**	-2.31	1,502	-0.028***	-3.75	520	-0.022	-1.39
(4) *Compustat values in BA actual value*	524	-0.144	-1.25	2,174	-0.144***	-3.84	542	-0.457***	-3.08

Panel B: Forecast Accuracy

Independent Variable: BondDummy	*Dependent Variable: Accu_CFO*			*Dependent Variable: Accu_EBITDA*			*Dependent Variable: Accu_EARN*		
	N	*Coeff.*	*t-stat*	*N*	*Coeff.*	*t-stat*	*N*	*Coeff.*	*t-stat*
(1) *Truncation at the top and bottom 1%*	342	0.807***	2.74	1,190	0.063***	2.85	434	-0.520***	-4.85
(2) *Last forecast as consensus*	422	0.898***	3.44	1,506	0.116***	4.38	522	-0.899***	-5.30
(3) *Prior year price as deflator*	420	-0.047	-0.96	1,502	0.024***	2.62	520	-0.109***	-6.42
(4) *Compustat values in BA actual value*	524	0.406***	2.66	2,174	0.158***	4.43	542	-0.942***	-5.63

This table contains the results on various robustness tests for H2 and H3. The regression is implemented for firm-year observations where bond analyst sample is matched with equity analyst sample. Refer to table 6 for more detail in the matching procedure. For brevity, only the coefficients on *BondDummy* are reported, although control variables are included in the regression models. Panel A presents the regression results for forecast bias comparison between bond and equity analysts and panel B presents the regression results for forecast accuracy comparison between bond and equity analysts. Year dummies are included, and standard errors are clustered by firm. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively, from two-tailed tests.