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Analyst Conflicts and Research Quality

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This paper examines whether the quality of stock analysts' forecasts is related to conflicts of interest from their employers' investment banking (IB) and brokerage businesses. We consider four aspects of forecast quality: accuracy, bias, and revision frequency of quarterly earnings per share (EPS) forecasts and relative optimism in long-term earnings growth (LTG) forecasts. Using a unique dataset that contains the annual revenue breakdown of analysts' employers among IB, brokerage, and other businesses, we uncover two main findings. First, accuracy and bias in quarterly EPS forecasts appear to be unrelated to conflict magnitudes after controlling for forecast age, firm resources, and analyst characteristics. Second, relative optimism in LTG forecasts and the revision frequency of quarterly EPS forecasts are positively related to the importance of brokerage business to analysts' employers. Additional tests suggest that the frequency of quarterly forecast revisions is positively related to analysts' trade generation incentives. Our findings suggest that reputation concerns keep analysts honest with respect to short-term earnings forecasts but not LTG forecasts. In addition, conflicts from brokerage appear to play a more important role in shaping analysts' forecasting behavior than has been previously recognized.

Keywords: Stock analysts; security analysts; analyst conflicts; analyst forecasts; investment banking; brokerage commissions; conflicts of interest.

1. Introduction

In April 2003, 10 of the largest Wall Street firms reached a landmark settlement with the New York State Attorney General, the US Securities and Exchange Commission (SEC), and other federal and state securities regulators on the issue of conflicts of interest faced by sell-side analysts. The firms agreed to pay a record $1.4 billion in penalties to settle government charges that their analysts had routinely issued optimistic stock research in order to win investment banking (IB) business from the companies they covered. Regulators cited the behavior of analysts such as Jack Grubman, perhaps the most influential telecom stock analyst during the late 1990s stock market boom. In November 1999, Grubman, then an analyst with Salomon Smith Barney, raised his rating on AT&T stock from a "hold" to a "strong buy" in an apparent bid to court AT&T's large IB business (see Gasparino, 2002).[1]

The settlement forced the participating securities firms to make structural changes in the production and dissemination of equity research (see Smith *et al.*, 2003). For example, analysts are no longer allowed to accompany investment bankers in making sales presentations, and securities firms are required to maintain separate reporting and supervisory structures for their research and IB operations. Firms must tie an analyst's pay to the quality and accuracy of his research rather than to the amount of IB business the research generates. In addition, an analyst's written report on a company must disclose whether his firm conducts IB business with the researched company.[2] Of the total settlement amount, $430 million was earmarked for providing investors with stock research from independent research firms.

The settlement was fundamentally grounded on the premise that analysts who are free from potential conflicts of interest produce superior, unbiased stock research. In this paper, we provide empirical evidence on whether the quality of analysts' research is related to the magnitude of their conflicts of interest. We focus on an important product of analyst research: forecasts of corporate earnings per share (EPS) and earnings growth. We address four questions. First, how is the accuracy of analysts' quarterly EPS forecasts

[1] Other instances of alleged conflicts of interest were commonplace. One example involved Phua Young, a Merrill Lynch analyst who followed Tyco International, Ltd. Merrill reportedly hired Young in September 1999 at the suggestion of Dennis Kozlowski, Tyco's then-CEO. Whereas the previous Merrill analyst had been highly critical of Tyco, Young embraced his role as a cheerleader for the company. See Maremont and Bray (2004).

[2] Throughout the paper, we refer to an analyst's employer as a "firm" and a company followed by an analyst as a "company".

related to the magnitude of conflicts with IB or brokerage business? Second, are conflicts related to the bias in quarterly forecasts? Third, how are conflicts related to the revision frequency of quarterly forecasts? And finally, what is the relation between analyst conflicts and relative optimism in long-term earnings growth (LTG) forecasts?

Answers to these questions are important not only to regulators and academics but also to a broad range of stock market participants. Retail and institutional investors alike use analyst reports to form expectations about the future prospects of a company. In fact, institutional investors seem to rely so much on analysts' opinions that they generally avoid investing in stocks without analyst coverage (see, e.g., O'Brien and Bhushan, 1990). Prior academic studies have found that analysts' earnings forecasts and stock recommendations have investment value (see, e.g., Givoly and Lakonishok, 1979; Stickel, 1991; Womack, 1996; Barber *et al.*, 2001; Jegadeesh *et al.*, 2004; Loh and Mian, 2006). Moreover, analysts are widely quoted in the news media on major corporate events, and their pronouncements on television can lead stock prices to respond within seconds (see Busse and Green, 2002).

To conduct our empirical analysis, we assemble a unique dataset that contains a breakdown of revenues for analyst employers (most of which are private firms not subject to the usual disclosure requirements for publicly traded companies) into revenues from IB, brokerage, and other businesses. This information allows us to examine in detail the relation between the quality of analyst research and potential conflicts arising from IB and brokerage businesses. We perform univariate and panel regression analyses using a sample of more than 170,000 quarterly EPS forecasts and more than 38,000 LTG forecasts for about 7400 US public companies during the January 1994 to March 2003 time period. These forecasts were issued by about 3000 analysts employed by 39 publicly traded securities firms and 124 private securities firms.

Prior academic research has focused on conflicts faced by analysts in the context of pre-existing underwriting relationships.[3] For instance, Lin and McNichols (1998) and Michaely and Womack (1999) find that analysts employed by underwriters in security offerings tend to be more optimistic than other analysts about the prospects of the issuing company. Kadan *et al.* (2009) document that recommendations of analysts whose employers

[3] See Ramnath *et al.* (2006) and Mehran and Stulz (2007) for excellent reviews of the literature on analyst conflicts.

have underwriting relationships with the covered companies are less optimistic and more informative following the enactment of recent US conflict-of-interest regulations. Our paper contributes to this line of research in several ways. First, our approach takes into account both actual as well as potential conflicts from IB activities. As long as an analyst's employer has an IB business, even if the employer does not *currently* do business with the followed company, it might aspire to do so in the future. Second, we examine the conflict of interest arising from IB in general, rather than solely from security offerings. In addition to offering underwriting services, an investment bank can offer advisory services on mergers and corporate restructuring. Third, while prior academic research, the news media, and regulators have generally focused on conflicts from IB business, our data allow us to examine conflicts from brokerage business as well. As discussed in Sec. 2 below, IB and brokerage operations are two distinct sources of potential conflicts of interest, and they may influence analyst behavior in different ways.

Fourth, the prior empirical finding that underwriter analysts tend to be more optimistic than other analysts is consistent with two distinct interpretations: (a) underwriter analysts issue optimistic reports on companies to reward them for past IB business or to curry favor to win future IB business, and (b) companies select underwriters whose analysts already have favorable views of their stocks to begin with. The second interpretation recognizes that underwriter choice is endogenous and that underwriter analyst optimism by itself does not necessarily imply a conflict of interest. We sidestep this issue of endogeneity by broadening the focus beyond the existence of underwriting relations between analyst employers and followed companies. Specifically, we capture the overall importance of IB and brokerage businesses to analyst employers by measuring the percentages of total annual revenues derived from these businesses. Unlike measures based on underwriting relations between analysts' employers and followed companies, the percentages of total revenues from IB or brokerage businesses are arguably exogenous in that they would be largely unaffected by an individual analyst's forecasting behavior. Finally, our approach yields substantially larger sample sizes than those used in prior research, leading to greater statistical reliability of the results.

Several papers study analyst conflicts using methods that are somewhat related to our approach. For example, Barber *et al.* (2007) find that recommendation upgrades (downgrades) by brokerage houses that have IB business underperform (outperform) similar recommendations by non-IB brokerages and independent research firms. Cowen *et al.* (2006) find that full-service securities firms, which have both IB and brokerage businesses, issue less optimistic forecasts and recommendations than do non-IB brokerage houses. Finally, Jacob *et al.* (2008) find that short-term earnings forecasts made by investment bank analysts are more accurate and less optimistic than those made by analysts at independent research firms. We extend this line of research by quantifying the reliance of a securities firm on IB and brokerage businesses. This is an important feature of our paper for at least two reasons. First, given that many securities firms operate in multiple lines of business, it can be difficult to unambiguously classify them according to business lines. By separately measuring the magnitudes of both IB and brokerage conflicts in each firm, our approach avoids the need to rely on a classification scheme. Second, since the focus of this research is on the consequences of analysts' conflicts, measuring the magnitude of conflict, and not simply its existence, is important. Our conclusions sometimes differ from classification-based studies.

Our main findings can be summarized as follows. We find no evidence that the accuracy or bias in individual analysts' quarterly EPS forecasts is related to the magnitude of their IB or brokerage conflicts, after controlling for forecast age, firm resources, analyst experience and analyst workload. This result also holds for technology stocks and during the late-1990s stock market boom, settings in which analysts may have faced particularly severe conflicts. The result holds for both publicly traded and private analyst employers, and it is robust to the use of alternate measures of conflict magnitude. However, we find that the importance of brokerage conflicts is positively related to both the level of LTG forecasts and the revision frequency of quarterly EPS forecasts. In further tests, we find that greater brokerage conflicts make it less likely that forecast revisions are intended to provide investors with timely and accurate information. That is, trade-generation motives appear to drive forecast revisions to a greater degree when brokerage conflicts are greater.

Our findings provide two important insights into the forecasting behavior of analysts who face potential conflicts of interest. First, while analysts do not appear to systematically respond to conflicts by biasing short-term (quarterly EPS) forecasts, they do appear to succumb to conflicts when making LTG forecasts. This difference may be because analysts are more concerned about a possible loss of reputation from issuing easily refuted short-term forecasts than from issuing LTG forecasts. Second, despite obvious instances of abuse that have been reported in the media, we find no systematic relationship between the magnitude of IB conflicts and several aspects of analysts' forecasting behavior. Brokerage conflicts, on the other hand, appear to play a more important role in shaping analysts' forecasting behavior than has been previously recognized.[4]

The remainder of the paper is organized as follows. Section 2 discusses the potential effects of conflicts of interest on analyst forecasts. Section 3 describes our sample and data. Section 4 presents our main empirical results. Section 5 examines two alternative explanations of our results on forecast revision frequency. Section 6 presents additional results from two partitions of the sample: the technology sector versus other industry sectors; and the late 1990s versus other time periods. Section 7 concludes.

2. Potential Effects of Conflicts of Interest

This section discusses the potential effects of conflicts of interest on four aspects of analysts' behavior and performance: accuracy, bias, and revision frequency of quarterly EPS forecasts, and optimism in LTG projections. Section 2.1 deals with IB conflicts, and Sec. 2.2 deals with brokerage conflicts.

2.1. *IB conflicts*

The most widely discussed type of analyst conflict arises from the fact that securities firms can use optimistic research to try to win or keep lucrative underwriting business.[5] Several academic studies have reported evidence of analyst optimism in the context of existing underwriting relationships. For example, Dugar and Nathan (1995) and Lin and McNichols (1998) find that analysts whose employers have underwritten seasoned equity offerings issue more favorable earnings forecasts and stock recommendations about clients than do non-underwriter analysts. Dechow *et al.* (2000) document a positive bias in underwriter analysts' LTG forecasts for firms conducting seasoned equity offerings. Michaely and Womack (1999) find that underwriter analysts

[4] In a companion paper (Agrawal and Chen, 2008), we find that analysts with greater IB and brokerage conflicts issue more positive stock recommendations, particularly during the late-1990s stock bubble. But the reactions of stock prices and trading volumes to recommendation revisions suggest that investors adjust for these biases by discounting the opinions of more conflicted analysts, even during the bubble. Furthermore, the one-year investment performance of recommendation revisions is unrelated to conflict magnitudes, suggesting that the marginal investor is not systematically misled by analyst advice. In related research, Malmendier and Shanthikumar (2007) show that while small investors appear to naively follow optimistic recommendations by underwriter analysts, institutions appear to rationally discount recommendations for underwriting bias.

[5] Ljungqvist *et al.* (2006, 2009) find that while optimistic recommendations do not help the analyst's firm win the lead underwriter or co-manager positions in general, they do help the firm win the co-manager position in deals where the lead underwriter is a commercial bank.

in initial public offerings are generally more optimistic in recommending a client firm's stock than are non-underwriter analysts, but underwriter recommendations exhibit particularly poor long-run stock performance. O'Brien *et al.* (2005) find that underwriter analysts in equity offerings are slower to downgrade stocks — but faster to upgrade them — than are non-underwriter analysts.

Securities firms seek not only to maintain the goodwill of existing IB clients, but also to attract new corporate clients. Corporate managers may award underwriting or merger advisory mandates to securities firms that issue consistently optimistic earnings forecasts. This incentive implies that EPS forecasts of analysts subject to pressure from IB should exhibit a more positive bias relative to forecasts of analysts at independent firms. Likewise, the long-term (three to five year) earnings growth estimates of analysts at IB firms should be rosier than the growth projections of independent analysts.

Alternatively, pressure from IB business can lead to a *pessimistic* bias in analyst forecasts. A widely held belief among market participants is that corporations often seek to meet or beat analysts' quarterly estimates, regardless of the absolute level of performance. Whether or not a company meets its quarterly estimates can serve as a rule of thumb by which boards of directors and investors evaluate managers (see, e.g., Degeorge *et al.*, 1999; Farrell and Whidbee, 2003). Indeed, Bartov *et al.* (2002) find that companies that exceed the threshold set by analyst estimates subsequently experience higher abnormal stock returns. Chan *et al.* (2007) document that the frequency of non-negative earnings surprises has grown in recent years, particularly for growth firms and for analysts employed by firms with no IB business. Therefore, "lowering the bar" with pessimistic forecasts, especially near the earnings announcement date, may be a way for conflicted analysts to win favor with potential IB clients.

If optimistic or pessimistic forecast biases are important, then, *ceteris paribus*, the overall accuracy of conflicted analysts should be lower than that of independent analysts. However, there are at least three mitigating forces that can reduce bias among analysts at large investment banks. First, compared to an independent research firm, an investment bank may provide an analyst with an environment that is more conducive to making high-quality forecasts. Possible advantages include access to greater resources and research support (Clement, 1999) and to information generated by the underwriting and due diligence process (Michaely and Womack, 1999). Second, firms with large IB operations can attract analysts with better forecasting ability. As Hong and Kubik (2003) find, more accurate analysts tend to move to more prestigious securities firms, which are more likely than small, regional firms to have significant IB operations.

Finally, reputation concerns can reduce analysts' response to IB conflicts. As in the model of Bolton *et al.* (2007), financial intermediaries that provide misleading advice to investors can suffer a loss of market share in the presence of competition from other information providers. Indeed, empirical evidence suggests that optimism in lead underwriters' stock recommendations is mitigated when a larger number of unaffiliated analysts cover the same stock (see Sette, 2011). It therefore stands to reason that an analyst who wants to avoid the risk of a tarnished reputation or loss of career prospects will be less inclined to issue biased and misleading earnings forecasts. Overall, then, the effect of IB conflicts on EPS and LTG forecasting behavior can be expected to depend on multiple and sometimes opposing forces. It is the net effect of these forces that we seek to understand in our empirical analysis below.

2.2. *Brokerage conflicts*

When a securities firm has significant brokerage operations, its analysts face direct or indirect incentives to use their research to generate trading commissions.[6] For example, an analyst may be able to increase his firm's trading volume by issuing optimistic projections.[7] A new earnings forecast that is particularly positive should lead to trading by both new investors and current shareholders, provided that investors ascribe at least some information content to the forecast. On the other hand, since short-sale constraints can prevent most investors from reacting to negative information unless they already hold a stock, a negative forecast should generate trading from a narrower set of investors.[8]

[6] Some brokerage firms acknowledge explicitly tying their analysts' compensation to the magnitude of trading commission revenues that their research generates. See, for example, the case of Soleil Research, Inc., discussed in Vickers (2003).

[7] Carleton *et al.* (1998) find that brokerage analysts appear to inflate their stock recommendations. Jackson (2005) shows theoretically that analysts' incentives for trade generation can lead to an optimistic forecast bias. Hayes (1998) develops a model to analyze how commission-based incentives and short-sale constraints can affect analysts' information gathering decisions. Ljungqvist *et al.* (2007) find that analysts employed by larger brokerages issue more optimistic recommendations and more accurate earnings forecasts.

[8] Numerous regulations in the US increase the cost of selling shares short (see Dechow *et al.*, 2001). Furthermore, traditional mutual funds that qualify as SEC-registered investment companies cannot derive more than 30% of their profits from short sales. Thus, it is not surprising that the vast majority of stock trades are regular purchases and sales rather than short sales. For example, over the 1994–2001 period, short sales comprised only about 10% of the annual New York Stock Exchange trading volume (see NYSE, 2002).

An analyst can also increase trading volume by revising his earnings forecasts frequently. Analysts' forecast revisions have been shown to increase share trading volume (see, e.g., Ajinkya *et al.*, 1991) and to significantly affect stock prices apart from earnings news, dividends, or other corporate announcements (see, e.g., Stickel, 1991). From one perspective, a positive relation between trading volume and the frequency of forecast revisions can be beneficial to investors. For example, if revising forecasts is costly, then analysts whose compensation is tied (directly or indirectly) to commission revenue may be more willing to issue timely revisions that reflect his changing earnings expectations. Indeed, previous work has established a link between analysts' forecasting frequency and their ultimate accuracy (see, e.g., Stickel, 1992; Clement and Tse, 2003).

However, the prospect of boosting commissions may lead an analyst to revise his forecasts too frequently even when there is little or no new information. This perverse "churning" behavior, despite being anticipated by rational investors, could be profitable for an analyst if investors assign a positive probability of genuine information content to the revisions.[9] If churning incentives are important, then one would expect that, relative to independent analysts, conflicted analysts will revise their forecasts more frequently and substantially and yet will not end up being more accurate.

As in the case of IB conflicts, concerns about loss of reputation can limit abusive analyst behavior stemming from brokerage conflicts. The importance of reputational concerns may depend on market conditions, on the time period in question, and on characteristics of analysts and their employers. Hence, the net relation between the magnitude of brokerage conflicts and the quality of LTG or quarterly EPS forecasts is ultimately an empirical issue.

3. Sample and Data

We obtain data on revenues of analyst employers from annual filings made with the SEC. Under Section 17 of the Securities Exchange Act of 1934, all registered broker-dealer firms in the United States, whether public or private, are required to file annual audited financial reports with the SEC. The requisite filings, referred to as x-17a-5 filings, must contain a statement of financial condition (balance sheet), a statement of income, a statement

[9] Irvine (2004), using transactions data from the Toronto Stock Exchange, documents that a brokerage firm's market share of trading in a stock tends to increase when its analyst issues a forecast further away from the consensus. He also finds, however, that greater forecast bias by itself does not increase market share.

of changes in financial condition, and a statement detailing net capital requirements.

Our sample construction begins with the set of all broker-dealer firms listed in the May 2003 version of Thomson Financial's I/B/E/S Broker Translation File, which contains 1257 entries. Of these entries, 159 correspond to forecast-issuing firms that chose to withhold their names from the Broker Translation File. For each of the remaining 1098 firms with names available, we conduct a manual keyword search for x-17a-5 forms using Thomson Financial's Global Access database and the public reading room of the SEC. Electronic form filing was first mandated by the SEC in 1994, so the availability of x-17a-5 filings before 1994 is extremely limited. Therefore, we restrict our sample to the 1994−2003 time period.

Out of the 1098 firms for which we have names, 318 firms did not file an x-17a-5 form with the SEC during our sample period, either because they were based in a jurisdiction outside of the US or because they were not active broker-dealers during the period. The filings for an additional 81 firms were not available electronically through Global Access. Finally, because the revenue breakdown of broker-dealers is a key data item used in this study, we exclude 454 firms for which this breakdown is not available. These firms chose to withhold the income statement portion of their x-17a-5 filings from the public under the SEC's confidential treatment provision.[10]

Because broker-dealer firms enter our sample only when they choose to publicly disclose their income statements, we face a potential sample selection bias if firms' tendency toward disclosure is systematically related to the nature of the firms' conflicts of interest. But this bias does not appear to be serious for our purposes for two reasons. First, the average levels of forecast characteristics of interest in this study (i.e., the bias, error, and revision frequency of quarterly EPS forecasts and the level of LTG estimates) are similar between private securities firms that either report or withhold their revenue breakdown information. Second, we conduct all of our main tests separately for forecasts issued by private broker-dealers and those issued by publicly traded broker-dealers. There is no selection bias for the latter subsample because all publicly traded firms are required to disclose their income statements in annual 10-K filings. The results for the two groups of firms are very similar.

[10] Under the Securities Exchange Act, broker-dealers are permitted to obtain confidential treatment of the income statement portion of an x-17a-5 filing if disclosure of the income statement to investors could harm the firm's business condition or competitive position.

The above selection procedure yields a sample of 245 firms. We further eliminate 20 instances in which the same firm appears in the Broker Translation File under multiple names or codes. Thus, for 225 unique firms we have data on total revenue and its key components for at least one year during the sample period.

We augment the sample by identifying all broker-dealer firms in I/B/E/S that were publicly traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or Nasdaq. Of the 44 firms identified as publicly traded, 21 firms do not disclose revenue information in their x-17a-5 filings. For these 21 firms, we use annual 10-K filings to gather financial data on revenues, revenue components, and balance-sheet items. Thus, the sample of firms for which we have revenue breakdown[11] data includes 246 broker-dealers, of which 44 are publicly traded. Of these, 163 broker-dealers (including 39 public companies) issued at least one forecast on I/B/E/S during our sample period.

Table 1 shows descriptive statistics for our sample of broker-dealers, analysts, and forecasts. Panel A describes the size and revenue breakdown for broker-dealers for the 2002 fiscal year. The first three columns are for the full sample, and the next three columns are for the sub-sample of publicly traded firms. The median securities firm is quite small, with total revenue of only \$3.25 million. The majority of firms have no IB revenue. The median revenue from brokerage commissions is \$1.6 million. Not surprisingly, the publicly traded securities firms in the sample are much larger, with median IB revenue of \$31 million and median brokerage commission revenue of \$50 million.

Panel B of Table 1 reports statistics, both for the full sample of firms and for the sub-sample of publicly traded firms, on the fraction of total revenue coming from either IB or brokerage commission. For the full sample of all firm-years, about half of the typical firm's total revenue comes from brokerage; the revenue from IB is negligible. The fraction of IB (brokerage) revenue ranges from 0 to 1 with a median of 0.004 (0.488) and mean of 0.112 (0.506). For the sub-sample of publicly traded securities firms, the corresponding range for the IB (brokerage) revenue fraction is from 0 (0.005) to 0.913 (0.999) with a median of 0.114 (0.362) and mean of 0.137 (0.393). Thus, compared to private securities firms, publicly traded firms derive a substantially greater proportion of their revenue from IB.

[11] Securities firms report revenue breakdown into revenues from investment banking, from brokerage, and from other businesses. The last category includes asset management, proprietary trading, market making, and margin lending.

Table 1. Sample characteristics.

Panel A: Broker-Dealer Firm Characteristics, 2002

	All Broker-Dealers			Public Broker-Dealers		
	Mean	Median	# of Firms	Mean	Median	# of Firms
Revenue ($ millions)	848.35	3.25	151	4953.32	176.15	25
Investment banking Revenue ($ millions)	97.28	0	151	572.17	30.73	25
Brokerage commission Revenue ($ millions)	154.16	1.60	151	847.06	49.80	25
Other revenue ($ millions)	596.90	0.43	151	3534.09	76.68	25

Panel B: IB and Commission Revenues Divided by Total Revenue, 1994−2003

	Distribution of the Fraction of Total Revenue							
Source of Revenue	N	Min	1st Quart.	Median	3rd Quart.	Max	Mean	Std. Dev.
All broker-dealers								
IB fraction	972	0	0	0.004	0.136	1	0.112	0.194
Brokerage fraction	972	0	0.207	0.488	0.853	1	0.506	0.341
Public broker-dealers								
IB fraction	227	0	0.069	0.114	0.154	0.913	0.137	0.137
Brokerage fraction	227	0.005	0.160	0.362	0.494	0.999	0.393	0.276

Panel C: Forecast Characteristics, 1994−2003

	Mean	Median	Sample Size	Unit of Observation
Bias in quarterly EPS forecasts				
One-month period	−0.00017	0.00026	54,369	Forecast
Three-month period	−0.00039	0.00027	171,915	Forecast
Inaccuracy in quarterly EPS forecasts				
One-month period	0.0037	0.0011	54,369	Forecast
Three-month period	0.0039	0.0011	171,915	Forecast
LTG forecasts (%)	19.61	16	38,209	Forecast
Number of quarterly earnings forecasts				
Over prior three months	1.325	1	188,658	Analyst-company-qtr.
Over prior six months	1.740	1	239,102	Analyst-company-qtr.

Table 1. (*Continued*)

Panel C (*Continued*)				
	Mean	Median	Sample Size	Unit of Observation
Forecast age (# of days)				
One-month period	14.001	14	59,699	Forecast
Three-month period	45.89	52	188,664	Forecast

Panel D: Analyst Characteristics, 1994−2003				
	Mean	Median	Sample Size	Unit of Observation
Company-specific forecasting experience (years)	2.25	1.11	87,244	Analyst-company-year
General forecasting experience (years)	4.32	2.97	9387	Analyst-year
Number of analysts employed by firm	76.55	61	9387	Analyst-year
Number of companies covered	10.19	9	9387	Analyst-year
Number of 4-digit I/B/E/S SIG industry groups covered	2.39	2	9378	Analyst-year

Note: This table provides descriptive statistics on broker-dealers, analysts, and forecasts. The sample includes I/B/E/S quarterly earnings and LTG forecasts made between January 1994 and June 2003 and corresponding annual financial information for broker-dealer firms. Panel A contains statistics on revenue components for broker-dealer firms for fiscal years ending in 2002. A broker-dealer is public if it is traded on the NYSE, Nasdaq, or AMEX. Panel B shows, over the sample period 1994−2003, the distribution of the fraction of total revenues generated from IB or brokerage businesses. N is the number of firm-years. Panel C reports characteristics of long-term growth forecasts and quarterly EPS forecasts over the entire sample period. Bias is computed as (actual EPS − forecast EPS) divided by the stock price 12 months before quarter-end. Forecast error is measured as the absolute value of forecast bias. Statistics for bias, accuracy and forecast age are based on the latest forecast made by each analyst over the relevant period. Forecast age is the number of days between a forecast date and earnings release. In Panels B and C, forecasts and broker-years are excluded when total revenues are negative or when fractions of revenue exceed one. In Panels B, C, and D, analyst teams and analysts for which forecasting experience could not be determined are excluded. In Panel C, the periods of one, three and six months refer to periods before quarter-end. Panel D reports analysts' experience and workload characteristics measured on an annual basis over the entire sample period.

We obtain forecasts and reported EPS numbers from the I/B/E/S US Detail History File for the time period from January 1, 1994 to June 30, 2003. All EPS forecasts and reported EPS numbers are converted to primary EPS numbers using the dilution factors provided by I/B/E/S. Our sample includes all quarterly EPS and LTG forecasts made by individual analysts working for broker-dealer firms for which we have revenue information; it excludes forecasts made by analyst teams.

In Panel C, characteristics of EPS and LTG forecasts are reported for the entire sample period. Following much of the literature on analysts' earnings forecasts, we compute forecast bias as the difference between actual EPS and forecasted EPS, divided by the stock price 12 months before quarter-end. We define forecast inaccuracy as the absolute value of forecast bias. Bias, inaccuracy, and forecast age are all computed from an analyst's latest forecast for a company during a quarter. The median EPS forecast is slightly pessimistic, but the magnitude of the pessimism is not large — roughly 1.3 cents on a $50 stock for forecasts made over the one-month or three-month period before quarter-end. The median forecast inaccuracy is much larger, about 5.5 cents on a $50 stock for both forecast periods. For LTG projections, the median forecast level is strikingly high, about 16% per year.[12] Over the three (six) month period preceding quarter-end, the median analyst following a company issues just one quarterly EPS forecast; the mean number of forecasts is 1.3 (1.7).

Panel D reports characteristics of individual analysts and their employers. The number of analysts employed by the analyst's firm, number of companies covered, and number of I/B/E/S industry groups covered, are all measured over the calendar year in which forecasts occur. We exclude analysts that are present in the EPS detail file in 1983 (the first year for which quarterly EPS forecasts are available through I/B/E/S) because we cannot fully observe the employment histories of these analysts. Overall, analysts in our sample do not appear to cover companies for long periods of time. The median company-specific forecasting experience of an analyst is about 1.1 years; his median general forecasting experience is about three years.[13] The median analyst works for a securities firm that employs 61 analysts and tracks nine companies in two different four-digit I/B/E/S S/I/G[14] industry groups.

Appendix Table A.1 lists, for fiscal year 2002, the largest analyst employers as well as the largest employers with either no IB or no brokerage business. As Panel A shows, Adams, Harkness, & Hill, Inc. is the largest employer in our sample without any IB business. The firm employs 23

[12] I/B/E/S defines a long-term growth forecast as the expected annual growth in operating earnings over a company's next full business cycle, usually a period of three to five years.

[13] Analyst experience appears to be short for several reasons. First, we only measure experience issuing quarterly EPS forecasts. Any additional experience issuing LTG forecasts or stock recommendations is not included in our measure. Second, securities firms hired a number of new analysts during the late 1990s stock market boom, a time period included in our sample. Third, company-specific forecasting experience is low because of large turnover in the portfolio of stocks followed by an analyst. This happens particularly after analysts change employers, which occurs quite frequently.

[14] Sector/Industry/Group code.

analysts and has total revenue of about $62 million, all of which consists of brokerage commissions.[15]

Analyst research is typically financed via a firm's brokerage business. Consequently, almost all sell-side analysts are employed by firms with at least some commission revenue. Analyst employers with no such revenue tend to be tiny boutique firms. Panel B indicates that there were only two such firms in 2002. Both firms were start-ups. One employed eight analysts, the other employed one. Finally, Panel C lists the five largest employers of analysts. Not surprisingly, these firms are among the most prominent and well-capitalized Wall Street securities firms. Merrill Lynch is the largest employer, employing 231 forecast-issuing analysts. Of Merrill Lynch's total 2002 revenues of $18.6 billion, $2.4 billion is from IB, $4.7 billion from brokerage commissions, and the rest from other businesses such as asset management and proprietary trading.

4. Empirical Results

We present our results on forecast accuracy in Sec. 4.1, forecast bias in Sec. 4.2, the level of LTG forecasts in Sec. 4.3 and revisions in quarterly forecasts in Sec. 4.4.

4.1. *Forecast accuracy*

We begin with univariate comparisons of forecast accuracy. Table 2 compares quarterly EPS forecast inaccuracy for analysts employed at firms with and without significant IB (or brokerage) business. We define a broker-dealer firm to have significant (insignificant) IB business if, at the end of the preceding fiscal year, its IB revenue as a percentage of its total revenue was in the top (bottom) quartile among all broker-dealers in the sample. A similar definition applies for brokerage commission business. All of the univariate comparisons are conducted at the level of the company. In other words, for each company in each quarter, we compute the mean forecast error for each type of securities firm; we then compare the resulting sets of matched pairs. Only the latest forecast made by an analyst during a quarter is used in the computation.

Panel A shows results for forecasts issued over the period of one month prior to quarter-end. Each set of two rows in the panel shows the mean and median values of our forecast accuracy measure for firms without and with

[15] Commission revenue slightly exceeds total revenue, which includes a loss from the firm's proprietary trading activities.

Table 2. Forecast accuracy of analysts employed by firms with versus without significant investment banking or brokerage business.

	A. One-Month Forecast Period			B. Three-Month Forecast Period		
Type of Firm	N	Mean	Median	N	Mean	Median
1. Firms with no significant IB business	3683	0.0029	0.0010	16,789	0.0032	0.0010
2. Firms with significant IB business	3683	0.0028	0.0010	16,789	0.0031	0.0010
p-value of t-test/signed-rank test (1 versus 2)		0.433	0.059		0.132	0.160
3. Firms with no significant brokerage business	3370	0.0026	0.0009	13,982	0.0029	0.0009
4. Firms with significant brokerage business	3370	0.0029	0.0010	13,982	0.0031	0.0010
p-value of t-test/signed-rank test (3 versus 4)		0.006	0.000		0.000	0.000
5. Firms with no significant IB and no significant brokerage business	998	0.0025	0.00078	4161	0.0024	0.0008
6. Firms with significant brokerage but with no significant IB business	998	0.0029	0.00082	4161	0.0028	0.0008
p-value of t-test/signed-rank test (5 versus 6)		0.056	0.025		0.002	0.000
7. Firms with no significant IB and no significant brokerage business	549	0.0026	0.00073	2837	0.0025	0.00082
8. Firms with significant IB but no significant brokerage business	549	0.0027	0.00073	2837	0.0023	0.00076
p-value of t-test/signed-rank test (7 versus 8)		0.818	0.581		0.024	0.084

Note: This table presents univariate comparisons of quarterly EPS forecast inaccuracy between different groups of analysts classified according to whether their employer has significant IB or brokerage business. Panel A (B) presents results for forecasts made within one (three) month(s) of quarter-end. Forecast inaccuracy is computed as the absolute value of (actual EPS − forecast EPS) divided by the stock price measured 12 months before quarter end. Forecasts are drawn from the January 1994–June 2003 period. A broker-dealer is defined to have significant (insignificant) IB business in a given calendar year if its IB revenue as a percentage of its total revenue is in the top (bottom) quartile among all broker-dealers in the sample. Significant or insignificant brokerage business is defined similarly based on commission revenue as a percentage of total revenue. Comparisons are conducted at the level of the company-year-quarter unit. For each publicly-traded company in the I/B/E/S US detail history file for which adequate data are available, forecast errors are averaged for each different type of broker-dealer firm; these averages are then compared using matched-pair t-tests for differences in means and Wilcoxon signed-rank tests for differences in distributions. N corresponds to the number of matched pairs. Only the latest forecasts made by individual analysts over the relevant forecast period are used. Revenue data are obtained from x-17a-5 or 10-K filings with the SEC. Forecasts are matched with annual broker-dealer financial data corresponding to the latest fiscal year preceding the date of the forecast.

significant IB (or brokerage) business. These are followed by a row showing p-values for differences between the two rows. The rows labeled 1 and 2 are for firms without and with significant IB business. The rows labeled 3 and 4 are for firms without and with significant brokerage business. Rows 5 and 6 and rows 7 and 8 conduct comparisons between firms with and without a particular type of business, conditional on the absence of the other type of business. The basic message from Panel A is that forecasts of analysts employed by firms with significant brokerage business (row 4) are somewhat less accurate than forecasts made by the control group of analysts (row 3). This finding holds even if IB business is insignificant (row 6 versus row 5).

Panel B shows corresponding results for forecasts made over the three-month period prior to quarter-end. Here, the results for firms with versus without significant brokerage operations mirror those in Panel A. In addition, analysts employed by firms with significant IB but no significant brokerage business (row 8) make forecasts that are somewhat more accurate than forecasts made by the control group of analysts (row 7).

We next conduct regression analyses linking forecast inaccuracy to our measures of conflict severity. In these regressions, we control for variables that have been found in prior research (e.g., Mikhail *et al.*, 1997; Clement, 1999; Jacob *et al.*, 1999) to affect analysts' forecast accuracy, such as forecast age, employer size, forecasting experience, and workload. Since the publicly traded and private securities firms in our sample likely differ in ways that are not fully captured by size, we also control for public versus private status. Our basic model is the following:

$$\begin{aligned}\mathrm{NAFE}_{ijt} = b_0 + b_1\mathrm{IB}_{it} + b_2\mathrm{COM}_{it} + b_3\mathrm{AGE}_{ijt} + b_4\mathrm{SIZE}_{it} + b_5\mathrm{CEXP}_{ijt} \\ + b_6\mathrm{GEXP}_{it} + b_7\mathrm{NCOS}_{it} + b_8\mathrm{NIND}_{it} + b_9\mathrm{PUBLIC}_{it} + e_{ijt},\end{aligned} \quad (1)$$

where the subscripts denote analyst i following company j for year-quarter t and the variables are defined as follows:

NAFE = Normalized absolute forecast error = forecast inaccuracy, as defined in Sec. 3,

IB (or COM) = IB (or commission) revenue as a percentage of total revenues of an analyst's employer,

AGE = Number of days between forecast date and earnings release,

SIZE = Natural log of one plus the number of analysts employed by a firm in year t,

CEXP = An analyst's company-specific forecasting experience = Number of years an analyst has been following the company,

GEXP = General experience as analyst = Number of years an analyst has been issuing forecasts to I/B/E/S,

NCOS = Number of companies followed by an analyst over the calendar year,

NIND = Number of different 4-digit I/B/E/S S/I/G industries followed by an analyst over the calendar year,

PUBLIC = 1, if a securities firm is publicly traded on NYSE, AMEX or NASDAQ, 0 otherwise, and

e = the error term.

The main explanatory variables of interest in Eq. (1) are our measures of conflicts faced by an analyst, IB and COM. These variables are measured at the level of a securities firm. We implicitly assume that from the perspective of an individual analyst, IB and COM are given, exogenous quantities that cannot be affected directly by the choice of a forecast. We use three alternative econometric approaches to estimate Eq. (1). The first approach is a pooled OLS regression, where t-statistics are computed using White's (1980) correction for heteroskedasticity. The unit of observation in the regression is an analyst-company-year-quarter (e.g., the Salomon analyst following IBM for the quarter ended March 2003). Our second approach follows Fama and MacBeth (1973), where we estimate cross-sectional regressions for each year-quarter and make inferences based on the time-series of coefficient estimates.[16] In both of these approaches, we include industry dummies as well as the natural logarithm of the followed company's market capitalization one year prior to quarter end. Finally, in the third approach, we estimate panel regressions where we treat company-year-quarter effects as fixed, because we are only interested in determining whether a particular analyst characteristic (namely, independence) is related to forecast inaccuracy. By focusing on differences across analysts following a given company for a given year-quarter (e.g., the March 2003 quarter for Microsoft), this approach avoids the need to control for characteristics of the company and the time period in question.[17] The regressions exclude a small number of observations for which an employer's total revenues are zero or negative due to securities trading losses.

Table 3 shows the results of our regressions on forecast inaccuracy. For each of the three estimation approaches, the table shows two variants of model

[16] In the Fama–MacBeth regressions reported in Tables 3 and 5, we exclude three quarters that have an insufficient number of observations to perform the estimation.

[17] See Wooldridge (2002) for an exposition of the fixed effects panel regression model. This approach has been employed by several studies of analyst forecasts (see, e.g., Clement, 1999; Agrawal *et al.*, 2006).

(1): one excluding the PUBLIC dummy variable and the other including it. Panel A (B) shows results for forecasts made within one month (three months) before quarter-end. Notably, the coefficients of the IB and COM variables are statistically indistinguishable from zero in all six estimations.[18] In other words, there is no indication in either panel that an analyst's forecast accuracy is related to the proportion of his employer's revenues coming from either IB or brokerage business.[19] While conflicts with IB or brokerage may affect the accuracy of analyst forecasts in particular cases, the effect does not show up systematically in the data. As expected, the regressions show that forecast inaccuracy is greater for older forecasts and is smaller for larger companies. There is only limited evidence that forecast inaccuracy is different for analysts employed by publicly traded versus private securities firms.

Table 3. Panel regression analysis of quarterly earnings forecast accuracy.

	Pooled OLS (1)		Fama–MacBeth (2)		Company-Quarter Fixed Effects (3)	
Panel A: One-Month Forecast Period						
Constant	−0.0083	−0.0083	−0.0040	−0.0049	0.0030	0.0030
	(−6.99)[a]	(−6.99)[a]	(−2.25)[b]	(−2.44)[b]	(8.82)[a]	(8.82)[a]
IB revenue as fraction of total revenue	−0.0009	−0.00089	−0.0015	0.0012	−0.00020	−0.00020
	(−0.67)	(−0.66)	(−1.10)	(0.52)	(−0.52)	(−0.52)
Commission revenue as fraction of total revenue	0.00036	0.00036	0.00076	−0.00018	0.00014	0.00014
	(0.76)	(0.75)	(1.82)	(−0.33)	(0.69)	(0.70)
Forecast age	0.00009	0.00009	0.00009	0.0001	0.00003	0.00003
	(9.15)[a]	(9.16)[a]	(8.07)[a]	(8.02)[a]	(7.18)[a]	(7.18)[a]
Ln (1 + Number of analysts employed by brokerage)	0.00015	0.00011	0.0002	0.00015	−0.00012	−0.00013
	(1.51)	(0.89)	(2.00)[b]	(1.19)	(−2.41)[b]	(−2.19)[b]
Company-specific forecasting experience * 10^{-3}	0.1799	0.1804	0.1750	0.1750	−0.0250	−0.0248
	(6.31)[a]	(6.31)[a]	(5.14)[a]	(5.23)[a]	(−1.81)	(−1.81)
General forecasting experience * 10^{-3}	−0.0552	−0.0558	−0.0276	−0.02667	0.034	0.0341
	(−2.27)[b]	(−2.28)[b]	(−1.36)	(−1.34)	(3.27)[a]	(3.27)[a]
Number of companies followed * 10^{-3}	0.00075	0.00067	0.0075	0.0086	−0.0041	−0.0041
	(−0.07)	(−0.06)	(0.51)	(0.58)	(−0.82)	(−0.83)

[18] The correlation between IB and COM is −0.17. Throughout the paper, results are similar when we include IB and COM variables one at a time in the regressions.

[19] These and subsequent results are generally similar when we replace the continuous IB and COM variables in each regression with binary dummy variables indicating either positive revenue or revenue over $10 million.

Table 3. (*Continued*)

	Pooled OLS (1)		Fama–MacBeth (2)		Company-Quarter Fixed Effects (3)	
Number of industry groups followed * 10^{-3}	0.0526 (0.81)	0.0538 (0.83)	−0.0222 (−0.29)	−0.0272 (−0.36)	−0.0421 (−1.47)	−0.0416 (−1.46)
Ln (Market capitalization of company)	−0.00127 (−18.71)[a]	−0.00127 (−18.63)[a]	−0.0013 (−14.54)[a]	−0.0013 (−14.57)[a]		
Public broker-dealer dummy		0.00018 (0.59)		0.0016 (2.25)[b]		0.00003 (0.25)
Number of observations	45,374	45,374	45,267	45,267	45,374	45,374
Number of groups					27,704	27,704
Model p-value	0.0000	0.0000			0.0000	0.0000
R^2	0.036	0.035	0.002	0.002	0.0043	0.0043
Panel B: Three-Month Forecast Period						
Constant	−0.0039 (−6.38)[a]	−0.0038 (−6.38)[a]	−0.0018 (−1.78)	−0.0029 (−2.64)[a]	0.0031 (20.21)[a]	0.0031 (20.19)[a]
IB revenue as fraction of total revenue	−0.00015 (−0.27)	−0.00015 (−0.28)	−0.0013 (−1.28)	0.0004 (0.26)	−0.00009 (−0.53)	−0.0001 (−0.53)
Commission revenue as fraction of total revenue	0.00019 (0.73)	0.00019 (0.74)	0.0005 (0.90)	0.00017 (0.66)	0.00004 (0.37)	0.00004 (0.38)
Forecast age	0.00003 (11.61)[a]	0.00003 (11.61)[a]	0.00003 (7.73)[a]	0.00003 (7.64)[a]	0.00002 (25.87)[a]	0.00002 (25.87)[a]
Ln (1 + Number of analysts employed by brokerage)	0.00017 (2.93)[a]	0.00013 (1.98)[b]	0.00015 (2.30)[b]	0.00006 (0.79)	−0.00011 (−4.41)[a]	−0.00011 (−3.91)[a]
Company-specific forecasting experience * 10^{-3}	0.1392 (5.86)[a]	0.1397 (5.85)[a]	0.1551 (6.06)[a]	0.00015 (6.04)[a]	−0.0153 (−2.13)[b]	−0.0155 (−2.12)[b]
General forecasting experience * 10^{-3}	−0.0021 (−0.12)	−0.0026 (−0.15)	0.00053 (0.04)	0.00039 (0.03)	0.0109 (2.08)[b]	0.0109 (2.07)[b]
Number of companies followed * 10^{-3}	−0.0315 (−5.40)[a]	−0.0315 (−5.40)[a]	−0.0203 (−2.06)[b]	−0.0194 (−1.97)[b]	−0.00146 (−0.59)	−0.00147 (−0.59)
Number of industry groups followed * 10^{-3}	0.0607 (1.67)	0.0617 (1.71)	0.0228 (0.46)	0.0198 (0.39)	−0.0193 (−1.33)	−0.0191 (−1.32)
Ln (Market capitalization of company)	−0.0015 (−32.69)[a]	−0.0015 (−32.67)[a]	−0.0014 (−20.39)[a]	−0.0014 (−20.44)[a]		
Public broker-dealer dummy		0.00014 (0.80)		0.0014 (3.02)[a]		0.00002 (0.30)

Table 3. (*Continued*)

	Pooled OLS (1)		Fama–MacBeth (2)		Company-Quarter Fixed Effects (3)	
Number of observations	143,477	143,477	143,318	143,318	143,477	143,477
Number of groups					61,996	61,996
Model p-value	0.0000	0.0000			0.0000	0.0000
R^2	0.026	0.026	0.001	0.001	0.009	0.009

[a,b]Denote statistical significance in two-tailed tests at the 1% and 5% levels, respectively.
Note: This table reports coefficient estimates from regressions explaining errors in individual analysts' quarterly EPS forecasts made over the January 1994–June 2003 period. Panel A (B) presents results for forecasts made within one (three) month(s) of quarter-end. Only company quarters ending in March, June, September, or December are included. Forecast and reported numbers are based on primary EPS. Forecast error is computed as the absolute value of (reported EPS − forecast EPS) divided by the stock price 12 months before quarter-end. For each forecast period, only the latest forecast made by an analyst is included. The regressions in (1) are pooled OLS regression estimates using White's correction for heteroskedasticity, and include industry and calendar-quarter dummies (not reported). Columns (2) report average coefficients obtained from Fama–MacBeth (1973) regressions performed on individual calendar quarters over the sample period. Each regression includes unreported industry dummies. In the fixed-effects regressions in (3), company-year-quarter effects are treated as fixed. Revenue data are obtained from x-17a-5 or 10-K filings with the SEC. Each forecast issued by an analyst is matched with broker-dealer revenue data corresponding to the latest fiscal year preceding the date of the forecast. Forecast age is measured as the number of days between the report date and the forecast date. Company-specific and general forecasting experience are measured as the number of years since an analyst first began issuing I/B/E/S EPS forecasts on a particular company or in general. The number of analysts employed by a firm, the number of companies covered by an analyst, and the number of industry groups covered by an analyst are measured over the calendar year of the earnings forecast. Industry groupings are based on I/B/E/S 4-digit S/I/G codes. Company market capitalization is measured in millions of dollars one year prior to quarter-end. The public brokerage dummy equals unity if a broker-dealer is traded on NYSE, AMEX, or Nasdaq and equals zero otherwise. T-statistics for coefficient estimates are in parentheses.

4.2. *Forecast bias*

Table 4 shows univariate comparisons, similar to the accuracy comparisons in Table 2, of forecast bias between different types of employers. Differences in mean bias between different employer types are mostly insignificant. Based on comparisons of median values, analysts at firms with significant IB (brokerage) business appear to be slightly more pessimistic (optimistic) in both forecast periods.

Table 5 shows estimated coefficients from regressions of forecast bias using the three econometric approaches employed in Table 3. The explanatory variables are the same as in Eq. (1). Here too, the unit of observation in the pooled OLS and fixed effects regressions is an analyst-company-year-quarter.

Table 4. Forecast bias of analysts employed by firms with versus without significant investment banking or brokerage business.

	A. One-Month Forecast Period			B. Three-Month Forecast Period		
Type of Firm	N	Mean	Median	N	Mean	Median
1. Firms with no significant IB business	3683	0.00007	0.0002	16,789	$-5.6*10^{-6}$	0.00026
2. Firms with significant IB business	3683	0.00011	0.0003	16,789	0.00003	0.00029
p-value of t-test/signed-rank test (1 versus 2)		0.747	0.028		0.493	0.0001
3. Firms with no significant brokerage business	3370	0.00003	0.00025	13,982	0.00008	0.00027
4. Firms with significant brokerage business	3370	−0.00013	0.00020	13,982	−0.00006	0.00025
p-value of t-test/signed-rank test (3 versus 4)		0.138	0.0005		0.017	0.000
5. Firms with no significant IB and no significant brokerage business	998	−0.0002	0.00022	4161	0.00026	0.00026
6. Firms with significant brokerage but with no significant IB business	998	−0.0002	0.00017	4161	0.00035	0.00029
p-value of t-test/signed-rank test (5 versus 6)		0.709	0.074		0.395	0.470
7. Firms with no significant IB and no significant brokerage business	549	−0.00037	0.0000	2837	0.00002	0.00022
8. Firms with significant IB but no significant brokerage business	549	−0.00044	0.0000	2837	0.00009	0.00025
p-value of t-test/signed-rank test (7 versus 8)		0.620	0.934		0.447	0.008

Note: This table presents univariate comparisons of quarterly EPS forecast bias between different groups of analysts classified according to whether their employer has significant IB or brokerage business. Panel A (B) presents results for forecasts made within one (three) month(s) of quarter-end. Forecast bias is measured as (reported EPS − forecast EPS) divided by the stock price measured 12 months before quarter end. Forecasts are drawn from the January 1994–June 2003 period. A broker-dealer is defined to have significant (insignificant) IB business in a given calendar year if its IB revenue as a percentage of its total revenue is in the top (bottom) quartile among all broker-dealers in the sample. Significant or insignificant brokerage business is defined similarly based on commission revenue as a percentage of total revenue. Comparisons are conducted at the level of the company-year-quarter unit. For each publicly traded company in the I/B/E/S US detail history file for which adequate data are available, forecast bias is averaged for each different type of broker-dealer firm; these averages are then compared using matched-pair t-tests for differences in means and Wilcoxon signed-rank tests for differences in distributions. N corresponds to the number of matched pairs. Only the latest forecasts made by individual analysts over the relevant forecast period are used. Revenue data are obtained from x-17a-5 or 10-K filings with the SEC. Forecasts are matched with annual broker-dealer financial data corresponding to the latest fiscal year preceding the date of the forecast.

Table 5. Panel regression analysis of quarterly earnings forecast bias.

	Pooled OLS (1)		Fama–MacBeth (2)		Company-Quarter Fixed Effects (3)	
Panel A: One-Month Forecast Period						
Constant	0.0045	0.0045	0.0050	0.0048	0.00086	0.00085
	(3.55)[a]	(3.54)[a]	(2.79)[a]	(2.59)[a]	(2.29)[b]	(2.27)[b]
IB revenue as fraction of total revenue	0.00088	0.00087	−0.00027	0.00026	0.00019	0.00019
	(0.64)	(0.63)	(−0.16)	(0.14)	(0.47)	(0.47)
Commission revenue as fraction of total revenue	−0.00017	−0.00016	−0.00097	−0.0006	−0.00019	−0.0002
	(−0.34)	(−0.32)	(−1.71)	(−1.09)	(−0.88)	(−0.92)
Forecast age	−0.00006	−0.00006	−0.00006	−0.00006	−0.00003	−0.00003
	(−5.67)[a]	(−5.68)[a]	(−4.52)[a]	(−4.51)[a]	(−5.76)[a]	(−5.78)[a]
Ln (1 + Number of analysts employed by brokerage)	0.00015	0.00023	0.00009	0.00025	0.00006	0.00009
	(1.49)	(1.93)	(0.65)	(1.52)	(1.16)	(1.48)
Company-specific forecasting experience * 10^{-3}	−0.1149	−0.1158	−0.1193	−0.1187	−0.0073	−0.0075
	(−3.86)[a]	(−3.89)[a]	(−3.18)[a]	(−3.18)[a]	(−0.49)	(−0.49)
General forecasting experience * 10^{-3}	0.0448	0.0458	0.0391	0.0381	0.026	0.0262
	(1.76)	(1.80)	(1.49)	(1.48)	(2.27)[b]	(2.28)[b]
Number of companies followed * 10^{-3}	−0.0125	−0.0126	−0.0211	−0.0219	−0.0038	−0.0037
	(−1.10)	(−1.11)	(−1.37)	(−1.46)	(−0.70)	(−0.68)
Number of industry groups followed * 10^{-3}	−0.060	−0.0621	−0.0492	−0.0474	−0.0737	−0.0754
	(−0.90)	(−0.93)	(−0.67)	(−0.65)	(−2.34)[b]	(−2.39)[b]
Ln (Market capitalization of company)	0.00024	0.00024	0.00028	0.00028		
	(3.48)[a]	(3.48)[a]	(3.72)[a]	(3.71)[a]		
Public broker-dealer dummy		−0.0003		−0.00026		−0.00013
		(−0.97)		(−0.79)		(−0.95)
Number of observations	45,374	45,374	45,267	45,267	45,374	45,374
Number of groups					27,704	27,704
Model p-value	0.0000	0.0000			0.0000	0.0000
R^2	0.008	0.008	0.001	0.001	0.003	0.003

Table 5. (*Continued*)

	Pooled OLS (1)		Fama–MacBeth (2)		Company-Quarter Fixed Effects (3)	
Panel B: Three-Month Forecast Period						
Constant	0.0025	0.0025	0.0021	0.0030	0.0002	0.0002
	(3.87)[a]	(3.86)[a]	(2.63)[a]	(3.28)[a]	(1.19)	(1.22)
IB revenue as fraction of total reveue	−0.00066	−0.00065	−0.0050	−0.0065	0.00016	0.00016
	(−1.18)	(−1.17)	(−1.08)	(−1.48)	(0.78)	(0.78)
Commission revenue as fraction of total revenue	−0.00012	−0.00012	−0.00054	−0.00024	0.00002	0.00003
	(−0.43)	(−0.44)	(−1.13)	(−0.75)	(0.21)	(0.24)
Forecast age	−0.00003	−0.00003	−0.00003	−0.00003	−0.00001	−0.00001
	(−9.39)[a]	(−9.39)[a]	(−6.04)[a]	(−6.01)[a]	(−14.88)[a]	(−14.89)[a]
Ln (1 + Number of analysts employed by brokerage)	0.00014	0.00017	0.00036	0.00042	0.00009	0.00008
	(2.33)[b]	(2.39)[b]	(2.31)[b]	(2.26)[b]	(3.36)[a]	(2.55)[b]
Company-specific forecasting experience * 10^{-3}	−0.0606	−0.0610	−0.0778	−0.0769	0.012	0.0121
	(−2.50)[b]	(−2.50)[b]	(−3.47)[a]	(−3.42)[a]	(1.47)	(1.49)
General forecasting experience * 10^{-3}	−0.0126	−0.0122	−0.0100	−0.0097	0.00343	0.0034
	(−0.73)	(−0.70)	(−0.70)	(−0.67)	(0.59)	(0.58)
Number of companies followed * 10^{-3}	0.0245	0.0245	0.0129	0.0121	−0.0019	−0.0195
	(4.07)[a]	(4.08)[a]	(1.36)	(1.27)	(−0.69)	(−0.70)
Number of industry groups followed * 10^{-3}	−0.0920	−0.0928	−0.0808	−0.0779	−0.0414	−0.041
	(−2.46)[b]	(−2.49)[b]	(−1.62)	(−1.56)	(−2.55)[b]	(−2.53)[b]
Ln (Market capitalization of company)	0.00035	0.00035	0.00043	0.00043		
	(7.68)[a]	(7.68)[a]	(5.99)[a]	(6.01)[a]		
Public broker-dealer dummy		−0.00011		−0.0011		−0.00004
		(−0.61)		(−2.72)[a]		(0.58)

Table 5. (*Continued*)

	Pooled OLS (1)		Fama–MacBeth (2)		Company-Quarter Fixed Effects (3)	
Number of observations	143,477	143,477	143,318	143,318	143,477	143,477
Model p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.005	0.005	0.001	0.001	0.003	0.003

[a,b]Denote statistical significance in two-tailed tests at the 1% and 5% levels, respectively.

Note: This table shows coefficient estimates from regressions explaining the degree of bias in individual analysts' quarterly EPS forecasts made over the January 1994–June 2003 period. Panel A (B) presents results for forecasts made within one (three) month(s) of quarter-end. Only company quarters ending in March, June, September, or December are included. Forecast and reported numbers are based on primary EPS. Forecast bias is computed as (reported EPS − forecast EPS) divided by the stock price 12 months before quarter-end. The sample includes only the latest forecast made by an analyst for a company during a given forecast period. Columns (1) show results of pooled OLS regressions that include industry and calendar-quarter dummies (not reported) and t-statistics using White's correction for heteroskedasticity. Columns (2) report average coefficient estimates from Fama–MacBeth (1973) regressions that include unreported industry dummies, performed on individual calendar quarters over the sample period. In the fixed-effects regressions in (3), company-year-quarter effects are treated as fixed. Revenue data are obtained from x-17a-5 or 10-K filings with the SEC. Each forecast issued by an analyst is matched with broker-dealer revenue data corresponding to the latest fiscal year preceding the date of the forecast. Forecast age is measured as the number of days between the report date and the forecast date. Company-specific and general forecasting experience are measured as the number of years since an analyst first began issuing I/B/E/S EPS forecasts on a particular company or in general. The number of analysts employed by a firm, the number of companies covered by an analyst, and the number of industry groups covered by an analyst are measured over the calendar year of the earnings forecast. Industry groupings are based on I/B/E/S 4-digit S/I/G codes. Company market capitalization is measured in millions of dollars one year prior to quarter-end. The public brokerage dummy equals one if a broker-dealer firm is publicly traded on NYSE, AMEX, or Nasdaq and equals zero otherwise. T-statistics for coefficient estimates are shown in parentheses.

In both panels, the coefficients of IB and COM variables are insignificant under each of the three estimation approaches. There is no evidence that an analyst's forecast bias is systematically related to the magnitude of potential conflicts with his employer's IB or brokerage business. Forecasts made earlier are more optimistic, consistent with the pattern found by prior studies (e.g., Brown *et al.*, 1985; Richardson *et al.*, 2004). An analyst's optimism increases with his company-specific forecasting experience and decreases with company size. All of these relations are statistically significant.

4.3. *LTG forecasts*

The univariate comparisons in Table 6 of long-term (three to five year) earnings growth forecasts reveal some notable differences. For example, mean

Table 6. LTG forecasts of analysts employed by firms with versus without significant IB or brokerage business.

Type of Firm	N	Mean	Median
1. Firms with no significant IB business	1508	20.74	17.88
2. Firms with significant IB business	1508	19.83	17.5
p-value of t-test/signed-rank test (1 versus 2)		0.002	0.112
3. Firms with no significant brokerage business	1578	18.58	15.9
4. Firms with significant brokerage business	1578	19.73	17
p-value of t-test/signed-rank test (3 versus 4)		0.000	0.000
5. Firms with no significant IB and no significant brokerage business	246	16.58	15
6. Firms with significant brokerage but with no significant IB business	246	17.83	15
p-value of t-test/signed-rank test (5 versus 6)		0.014	0.001
7. Firms with no significant IB and no significant brokerage business	52	19.40	20
8. Firms with significant IB but no significant brokerage business	52	21.66	20
p-value of t-test/signed-rank test (7 versus 8)		0.033	0.016

Note: Univariate comparisons of long-term (3 to 5 years) growth forecasts between different groups of analysts classified according to whether their employer has significant IB or brokerage businesses. The sample period is from January 1994 through June 2003. A broker-dealer is defined to have significant (insignificant) IB business in a given calendar year if its IB revenue as a percentage of its total revenue is in the top (bottom) quartile among all broker-dealers in the sample. Significant or insignificant brokerage business is defined similarly based on commission revenue as a percentage of total revenue. Comparisons are conducted at the level of the company-year-quarter unit. For each publicly traded company in the I/B/E/S US detail history file for which adequate data are available, LTG forecast levels are averaged for each different type of broker-dealer firm; these averages are then compared using matched-pairs t-tests for differences in means and Wilcoxon signed-rank tests for differences in distributions. N corresponds to the number of matched pairs. Only the latest company forecast made by an individual analyst over the appropriate quarter (March, June, September, or December) is used. Revenue data are obtained from x-17a-5 or 10-K filings with the SEC. Forecasts are matched with annual broker-dealer financial data corresponding to the latest fiscal year preceding the date of the forecast.

growth forecasts are slightly less optimistic for analysts employed by firms with significant IB business (row 2) compared to the control group of analysts (row 1). For analysts employed by firms with substantial brokerage business (rows 4 or 6), LTG forecasts are higher than forecasts of the control group. For analysts employed by firms with significant IB but insignificant brokerage business (row 8), LTG forecasts are higher than forecasts for the control group (row 7). But the sample sizes in this last comparison are quite small, so they do not warrant strong conclusions.

Table 7 shows the results of Fama−MacBeth regressions and fixed effects regressions explaining LTG levels. We do not use pooled OLS regressions here because of a natural quarter-to-quarter serial dependence in the level of growth forecasts for a company. The unit of observation in the panel regressions is an analyst-company-year-quarter. The explanatory variables are the same as in Eq. (1), except that the forecast AGE variable is no longer relevant and hence excluded. In the fixed effects regressions, the level of analysts' LTG forecasts increases with the proportion of their employers' revenues from brokerage business (COM). The magnitude of this effect is non-trivial. For instance, an increase in COM from the first to the third quartile of the sample is associated with an increase in the level of LTG of about 0.82%.[20] The level of LTG forecasts decreases with the size of the analyst's employer. In the Fama−MacBeth regressions, the level of LTG forecasts decreases in an analyst's company-specific forecasting experience and the number of companies followed by the analyst; it increases in the number of industry groups the analyst follows. All these relations are statistically significant.

4.4. *Frequency of forecast revision*

Table 8 shows results of panel regressions explaining a fourth aspect of analysts' forecasts, namely, the frequency of quarterly EPS forecast revisions. The dependent variable in the OLS specification (column (1)) and the Poisson specification (column (3)) is the number of EPS forecasts an individual analyst issues for a given company during the three-month period preceding the end of a quarter. The dependent variable in the logistic regressions (column (2)) is an indicator variable that equals one if an analyst issues multiple forecasts during the period; it equals zero otherwise. The unit of observation in the regressions

[20] While an increase in the annual earnings growth rate of 0.8% may seem inconsequential, equity values (e.g., in dividend growth models) tend to be quite sensitive to even small changes in expectations of growth rates of dividends and earnings.

Table 7. Analysis of LTG forecasts.

	Fama–MacBeth (1)		Company-Quarter Fixed Effects (2)	
Constant	20.17	17.33	21.54	21.58
	(3.16)[a]	(2.37)[b]	(28.87)[a]	(28.64)[a]
IB revenue as fraction of total revenue	3.53	8.86	0.151	0.158
	(0.29)	(0.61)	(0.14)	(0.15)
Commission revenue	6.68	−2.16	1.27	1.257
as fraction of total revenue	(0.64)	(−0.68)	(2.39)[b]	(2.37)[b]
Ln (1 + Number of analysts	−0.498	−0.22	−0.516	−0.543
employed by brokerage)	(−0.65)	(−0.27)	(−3.61)[a]	(−3.28)[a]
Company-specific forecasting experience	−0.649	−0.65	0.026	0.026
	(−17.03)[a]	(−16.90)[a]	(0.78)	(0.79)
General forecasting experience	−0.003	−0.005	−0.005	−0.005
	(−0.08)	(−0.15)	(−0.26)	(−0.27)
Number of companies followed	−0.032	−0.034	−0.007	−0.007
	(−2.05)[b]	(−2.11)[b]	(−0.73)	(−0.74)
Number of industry groups followed	0.185	0.185	0.035	0.035
	(3.03)[a]	(2.97)[a]	(0.54)	(0.54)
Public broker-dealer dummy		3.459		0.090
		(1.05)		(0.32)
Number of observations	35,258	35,258	35,319	35,319
Number of groups			26,870	26,870
R^2	0.008	0.008	0.007	0.007

[a,b]Denote statistical significance in two-tailed tests at the 1% and 5% levels, respectively.
Note: This table reports coefficient estimates from regressions explaining the level of LTG forecasts made over the January 1994–June 2003 period. The sample period is partitioned into calendar quarters ending March, June, September and December. The sample includes only the latest forecast made in a quarter by an analyst for a company. The Fama–MacBeth regressions include unreported industry dummies. In the fixed-effects regressions, company-year-quarter effects are treated as fixed. Revenue data are obtained from x-17a-5 or 10-K filings with the SEC. Each forecasting period is matched with broker-dealer revenue data corresponding to the latest fiscal year preceding the date of the forecast. Company-specific and general forecasting experience are measured as the number of years since an analyst first began issuing I/B/E/S EPS forecasts on a particular company or in general. The number of analysts employed by a firm, the number of companies covered by an analyst, and the number of industry groups covered by an analyst are measured over the calendar year of the earnings forecast. Industry groupings are based on I/B/E/S 4-digit S/I/G codes. The public brokerage dummy equals unity if a broker-dealer is traded on NYSE, AMEX, or Nasdaq and equals zero otherwise. *T*-statistics for coefficient estimates are in parentheses.

is an analyst-company-year-quarter. All three specifications include industry and year-quarter dummies.[21] The explanatory variables are the same as in

[21] We do not treat company-year-quarter effects as fixed here because doing so results in the loss of a large number of groups with no variation in the dependent variable.

Table 8. Analysis of quarterly earnings forecast frequency.

	OLS Specification (1)		Logistic Specification (2)		Poisson Specification (3)	
Constant	1.4321	1.4324	−0.9397	−2.2965	0.3521	0.0784
	(17.29)[a]	(17.29)[a]	(−3.38)[a]	(−6.37)[a]	(5.94)[a]	(1.32)
Commission revenue as fraction of total revenue	0.0606	0.0607	0.2008	0.1995	0.0465	0.0467
	(6.75)[a]	(6.77)[a]	(5.49)[a]	(5.46)[a]	(6.81)[a]	(6.84)[a]
Ln (1 + Number of analysts employed by brokerage)	0.0140	0.0121	0.0838	0.0895	0.0114	0.0101
	(6.67)[a]	(4.79)[a]	(9.56)[a]	(8.56)[a]	(7.11)[a]	(5.27)[a]
Company-specific forecasting experience	0.0088	0.0088	0.0265	0.0265	0.0062	0.0062
	(12.51)[a]	(12.53)[a]	(10.75)[a]	(10.71)[a]	(12.12)[a]	(12.14)[a]
General forecasting experience	−0.0015	−0.0016	−0.0049	−0.0049	−0.0011	−0.0011
	(−3.24)[a]	(−3.29)[a]	(−2.63)[a]	(−2.59)[a]	(−3.16)[a]	(−3.20)[a]
Number of companies followed	0.0011	0.0011	0.0042	0.0042	0.0009	0.0009
	(6.39)[a]	(6.39)[a]	(5.70)[a]	(5.70)[a]	(6.64)[a]	(6.64)[a]
Number of industry groups followed	−0.0080	−0.0079	−0.0268	−0.0270	−0.0060	−0.0059
	(−7.91)[a]	(−7.86)[a]	(−6.26)[a]	(−6.30)[a]	(−7.74)[a]	(−7.69)[a]
Ln (Market capitalization of company)	0.0291	0.0291	0.1071	0.1072	0.0222	0.0221
	(30.67)[a]	(30.65)[a]	(28.75)[a]	(28.76)[a]	(31.15)[a]	(31.12)[a]
Public broker-dealer dummy		0.0077		−0.0230		0.0052
		(1.46)		(−1.00)		(1.27)
Number of observations	143,474	143,474	143,474	143,474	143,474	143,474
Model p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R^2	0.067	0.067	0.045	0.045	0.008	0.008

[a,b]Denote statistical significance in two-tailed tests at the 1% and 5% levels, respectively.

Note: The dependent variable in the OLS and Poisson regressions in columns (1) and (3) is the number of EPS forecasts issued by an individual analyst on a given company during the three months preceding the end of the quarter. The dependent variable in the logistic regressions in column (2) is an indicator variable equal to one if an analyst issued more than one forecast during the three-month forecasting period, and equal to zero otherwise. The sample consists of quarterly EPS forecasts made over the January 1994−June 2003 period. Company quarters not ending March, June, September, or December are excluded from the analysis. Regressions are performed on the pooled sample of observations and include unreported industry and calendar-quarter dummies. Revenue data from x-17a-5 or 10-K filings with the US SEC are used to construct a variable measuring the potential degree of analysts' conflict of interest. Each forecast period is matched with broker-dealer revenue data corresponding to the latest fiscal year ending before the forecast period. Company-specific and general forecasting experience are measured as the number of years since an analyst first began issuing EPS forecasts through I/B/E/S on a particular company or in general. The number of analysts employed by a firm, the number of companies covered by an analyst, and the number of industry groups covered by an analyst are measured over the calendar year of the earnings forecast. Industry groupings are based on I/B/E/S 4-digit S/I/G codes. Company market capitalization is measured in millions of dollars one year prior to quarter-end. The public brokerage dummy equals unity if a broker-dealer is traded on NYSE, AMEX, or Nasdaq and equals zero otherwise. Heteroskedasticity-consistent t-statistics and z-statistics are in parentheses.

Eq. (1), except that the IB and AGE variables are excluded because we have no *a priori* reason to expect a systematic relation between these variables and the frequency of forecast revision. *T*-statistics are computed using White's correction for heteroskedasticity.

Under each of the three specifications, we find that analysts employed by firms with greater proportions of revenue from brokerage business (COM) issue more frequent forecast updates over the course of the quarter. This result is highly statistically significant. Moreover, the magnitude of this effect appears to be non-trivial. For example, in the OLS specification, an increase in COM from the first to the third quartile of the sample leads to an increase of about 0.04 in the number of forecasts, or about 3% of the sample mean. Table 8 also reveals that an analyst is likely to revise his forecast more often when the followed company is larger, when his employer is larger, when he has more company-specific forecasting experience, when he follows more companies, when he has less general forecasting experience, or when he covers fewer industries. All of these relations are statistically significant.

5. Interpretation of Results on Forecast Revision Frequency

As discussed in Sec. 2.2, the positive relation we find between COM and forecast revision frequency in Sec. 4.4 is consistent with two distinct motives. On one hand, an analyst who is compensated for generating commission revenue should be more willing to devote time and effort to making timely forecast revisions that reflect updated expectations about earnings. We refer to this as the "investor welfare" motive. Alternatively, the prospect of boosting commissions can lead an analyst to revise his forecasts frequently even with little or no new information. Frequent forecast revisions can be particularly effective in getting investors to churn their portfolios if the absolute magnitudes of successive changes in forecasts are large. We call this the "churning" motive. While the investor welfare and churning motives are not mutually exclusive, the first is consistent with maximization of investors' interests, and the second is not. We attempt to distinguish between these two motives by conducting three tests, presented in Secs. 5.1 through 5.3.

5.1. *Commission incentives, earnings uncertainty, and revision frequency*

As a first test of the two motives for making frequent forecast revisions, we add a measure of earnings uncertainty to the explanatory variables in Table 8 regressions of forecast revision frequency. The more uncertain a company's earnings for a given quarter, the greater will be investor demand for frequent forecast updates. Following Johnson (2004), we measure earnings uncertainty by the dispersion (i.e., standard deviation) of analyst forecasts at the beginning of the quarter. A positive coefficient on forecast dispersion would tend to confirm the investor welfare motive. At the same time, if the coefficient of COM is still positive after controlling for dispersion, this finding would be consistent with the churning motive.

We find that the coefficients of both forecast dispersion and COM are positive and statistically significant at the 0.001 level or better in the extended versions of all six models in Table 8. Our evidence thus suggests that the frequency of forecast updates is partly driven by investor demand for updated information. But, after controlling for this effect, commission incentives still play an important role in an analyst's decision on how frequently to revise his forecast. To save space, we do not report these results in a table.

5.2. *Commission incentives and churning*

For our second test of the motives underlying frequent forecast revisions, we devise two simple measures of churning,[22] denoted CHURN_1 and CHURN_2, and estimate the following regression:

$$\text{CHURN}_{ijt} = b_0 + b_1\text{COM}_{it} + b_2\text{SIZE}_{it} + e_{ijt}, \tag{2}$$

where the subscripts denote Analyst i following Company j for Year-quarter t, COM and SIZE are as defined as in Sec. 4.1, and the churning measure is defined as follows:

$\text{CHURN} = \text{CHURN}_1$ or CHURN_2,

$\text{CHURN}_1 =$ Mean absolute forecast revision $= \sum_{k=2}^{n} |d_k - d_{k-1}|/(n-1)$,

$\text{CHURN}_2 =$ Mean squared forecast revision $= \sum_{k=2}^{n} (d_k - d_{k-1})^2/(n-1)$,

$d_k = F_k/S$,

$F_k = k$th forecast of EPS made by an analyst for a given company-year-quarter,

$S =$ Stock price 12 months before quarter-end,

$n =$ Number of forecasts made by an analyst for a given company-year-quarter over the six-month period prior to quarter-end, and

$e =$ the error term.

The churning story suggests that the stronger is the commission incentive, the larger should be the absolute magnitude of successive changes in

[22] Both measures capture a salient aspect of churning, namely the average distance between successive changes in an analyst's forecast, without regard to gains in forecast accuracy.

forecasts. This implies that the coefficient b_1 in Eq. (2) should be positive. On the other hand, the investor welfare story, under which forecast revisions are aimed purely at providing updated information to investors in a timely fashion, implies no particular relation between the strength of commission incentives and the magnitude of successive changes in an analyst's forecasts.

We estimate Eq. (2) in a pooled OLS regression with robust standard errors. The estimate of the coefficient b_1 is significantly positive using either CHURN_1 or CHURN_2 as the dependent variable, with t-values of 2.68 and 2.81, respectively. In other words, the average magnitude of changes in an analyst's forecasts appears to be positively related to the strength of brokerage conflicts.

These churning variables measure the magnitude, rather than the frequency, of successive forecast revisions by an analyst. We next examine churning measures that take into account both, by multiplying each measure by $(n-1)$. We then re-estimate Eq. (2) as earlier. Once again, the estimate of the coefficient b_1 is significantly positive, with t-values of 4.62 and 3.08, respectively, for the two churning measures. Overall, this evidence is consistent with the idea that analysts employed by firms where brokerage business is more important issue forecast updates that are more frequent and larger in magnitude in an attempt to generate trades. These results are not shown in a table to save space.

5.3. *Boldness, trade generation, and forecast accuracy*

One characteristic of a forecast revision that is generally related to both accuracy and trade generation is boldness, i.e., how much the new forecast departs from the consensus. Compared to forecasts that herd with the consensus, bold forecasts tend to be more accurate (see, e.g., Clement and Tse, 2005), and they generate more trades for the analyst's firm (Irvine, 2004). In addition, Clement and Tse find that a bold revision tends to be more accurate than the original forecast. Motivated by these prior findings, we conduct tests examining the link between the boldness of a revised forecast and the incremental change in forecast accuracy for analysts facing different degrees of brokerage conflicts. Specifically, we estimate the following pooled regression by OLS:

$$\begin{aligned}\Delta\text{NAFE}_{ijt} = {} & b_0 + b_1\text{BOLDNESS}_{ijt} * \text{HCOM}_{it} \\ & + b_2\text{BOLDNESS}_{ijt} * \text{LCOM}_{it} + b_3\text{NDAYS}_{ijt} + e_{ijt},\end{aligned} \tag{3}$$

where the subscripts denote analyst i following company j for year-quarter t, NAFE is forecast inaccuracy as defined in Sec. 4.1, and the other variables are defined as follows:

$\Delta\text{NAFE}_{ijt} = \text{NAFE}_{ijt} - \text{NAFE}_{ij,t-1}$,
$\text{BOLDNESS}_i = |F_i - F|/S$,
F_i = Forecast of analyst i for a given company-year-quarter,
F = Consensus forecast for the company-year-quarter,
S = Stock price 12 months before quarter-end,
$\text{HCOM}_i = 1$, if analyst i works for an employer with high (above-median) COM,
$= 0$ otherwise,
$\text{LCOM}_i = 1 - \text{HCOM}_i$,
NDAYS = Number of days between the current forecast and prior forecast of an analyst about a company-year-quarter, and
e = the error term.

The investor welfare story predicts that $b_1 = b_2 < 0$, while the churning story predicts that $b_1 > b_2$. In other words, if forecast revisions are aimed purely at providing timely and accurate information to investors, then the relation between forecast inaccuracy and boldness should be negative and of the same magnitude for analysts facing high or low degrees of brokerage conflicts. But if frequent revisions are at least partly aimed at inducing investors to churn their portfolios, then the relation between forecast inaccuracy and boldness should be less negative for analysts who face higher degrees of brokerage conflict.

Our estimation of Eq. (3) indicates that $\hat{b}_1 = -0.13$ and $\hat{b}_2 = -0.31$; both coefficients are significantly different from zero. The test of the null hypothesis that $b_1 = b_2$ has an associated p-value of less than 0.0001. In other words, bold forecast revisions do tend to increase forecast accuracy, but this gain in accuracy is significantly greater for analysts with lower brokerage conflicts. These results suggest that, although the investor welfare story holds, churning is also an important motive for forecast revisions. We obtain qualitatively similar results if we replace the boldness variable by the change in boldness or if we replace the continuous measure of boldness in Eq. (3) with a binary measure used in Clement and Tse (2005). Once again, we do not show these results in a table to save space.

6. Sub-Sample Results

We next examine two interesting partitions of our sample. We present the results for technology versus other sectors in Sec. 6.1 and the results for the late 1990s versus other time periods in Sec. 6.2.

6.1. *Technology versus other industry sectors*

Numerous stories in the media suggest that conflicts of interest may have been more pronounced in the technology sector than in other industry sectors during our sample period. We examine this idea by replacing the IB variable in model (1) of Tables 3, 5, and 7 by two variables, IB*TECH and IB*NTECH, and replacing the COM variable in Tables 3, 5, 7, and 8 by COM*TECH and COM*NTECH. The binary variable TECH equals 1 if the first two digits of the I/B/E/S S/I/G code of a followed company are "08" (i.e., the company belongs to the technology sector); otherwise, TECH equals zero. NTECH is defined as 1 − TECH.

We find no significant relation between the accuracy and bias in an analyst's quarterly earnings forecasts and the importance to his employer of IB or brokerage business either in the technology sector or in other industry sectors. The frequency of an analyst's forecast updates is positively related to the importance of brokerage business to his employer in each sector, with no significant difference in the coefficient estimates. But the level of analysts' long-term growth (LTG) forecasts is positively related to the importance of IB and brokerage business only for the technology sector; it is insignificant for the remaining sectors as a group. This difference is statistically significant. To save space, we do not tabulate these results.

6.2. *Late 1990s versus other time periods*

The late 1990s was a period of booming stock prices. Media accounts and the timing of regulatory actions suggest that conflicts of interest were particularly severe during this period. To examine this idea, we replace the IB variable in model (1) of Tables 3, 5, and 7 by two variables: IB*LATE90S and IB*NLATE90S. Similarly, we replace the COM variable in Tables 3, 5, 7, and 8 by COM*LATE90S and COM*NLATE90S. The variable LATE90S equals 1 for forecasts made for time periods ending during 1995−1999; it equals zero otherwise. NLATE90S equals 1 − LATE90S.

There is no significant relation between the accuracy or bias in an analyst's quarterly earnings forecasts and the importance to his employer of IB or brokerage business for either the late 1990s or other time periods in our sample. The level of LTG forecasts is unrelated to IB during both time periods. LTG is positively related to COM during the late 1990s and is unrelated to it during other time periods, but the difference is statistically insignificant. The probability of forecast revision is positively related to COM during both time periods, but the coefficient of COM is significantly lower during the late 1990s than during other periods. Once again, we do not show these results in a table to save space.

7. Summary and Conclusion

The landmark settlement that prominent Wall Street firms reached with regulators in April 2003 mandated sweeping changes in the production and dissemination of sell-side analyst research. Among its key provisions, the settlement required securities firms to create and maintain greater separation between equity research and IB activities, and to provide brokerage customers with research reports produced by independent research firms. The basic premise underlying such requirements is that independent analysts do in fact produce research that is superior to that of analysts who face potential conflicts of interest from their employers' other businesses.

In this paper, we empirically examine whether the quality of analysts' forecasts of earnings or earnings growth is related to the magnitude of potential conflicts of interest arising from their employers' IB and brokerage businesses. Using a unique dataset containing the breakdown of securities firms' revenues from IB, brokerage, and other businesses, we investigate the effects of analyst conflicts on four aspects of their forecasts: accuracy and bias in quarterly earnings forecasts, optimism in LTG forecasts, and the frequency of quarterly forecast revisions.

Our investigation reveals that quarterly EPS forecast bias and accuracy do not appear to be systematically related to the importance of IB or brokerage business to analysts' employers. This result also holds for forecasts made for companies within the technology sector as well as forecasts made during the late-1990s stock market boom, contexts in which conflicts of interest may have been particularly severe. In addition, the absence of a link between analyst conflicts and quarterly forecast bias or accuracy holds for publicly traded as well as private analyst employers, and it is robust to several alternative measures of conflict severity.

We find, however, that the degree of relative optimism in analysts' LTG forecasts tends to increase with the share of their employers' revenues derived from brokerage commissions. We also find that the frequency of forecast revisions bears a significant positive relationship with the share of revenues from brokerage business. We conduct several tests to distinguish between alternative explanations of this finding. The results of these tests suggest that analysts' trade generation incentives can indeed impair the quality of stock research. Our findings imply that distortions in analyst research are unlikely to be completely eliminated by regulations that focus solely on IB conflicts. The precise nature of trade generation incentives, how they impact analyst behavior, and how they might be mitigated all appear to be fruitful avenues for future research.

Our findings also highlight a key difference in analysts' short-term (quarterly EPS) versus long-term (EPS growth) forecasting behavior. While analysts do not appear to systematically respond to conflicts by biasing short-term forecasts, they do appear to succumb to conflicts when making long-term growth projections. What accounts for this difference? One possibility is that short-term forecasts allow the labor market to assess an analyst's performance against an objective, well-defined benchmark. If an analyst allows his short-term forecasts to be affected by the conflicts he faces, his deception can be revealed with the very next earnings release, damaging his reputation and livelihood. But with long-term forecasts, analysts may not face the same degree of market scrutiny. Investors' memories may be short, and analysts may be able to get away with revising their initial flawed projections. A second possible explanation, suggested by dividend growth models, is that equity valuations depend more on long-term growth rates than on the next quarter's earnings, and analysts use the most effective means available to prop up a stock. We leave a complete resolution of this issue to future research.

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Appendix

Table A.1. Firms employing the most analysts for fiscal years ending in 2002.

Panel A: Largest Analyst Employers with No IB Business

Firm Name	Number of Analysts	Total Revenue ($ Millions)	Commission Revenue ($ Millions)
Adams, Harkness, & Hill, Inc.	23	61.78	63.84
BB&T Capital Markets	21	52.31	9.01
SWS Securities	17	22.78	22.42
Buckingham Research	17	28.69	27.23

Panel B: Largest Analyst Employers with No Commission Revenue

Firm Name	Number of Analysts	Total Revenue ($ Millions)	IB Revenue ($ Millions)
Paradigm Capital, Inc.	8	0.0017	0
Hudson River Analytics, Inc.	1	0.0014	0

Panel C: Largest Analyst Employers

Firm Name	Number of Analysts	Total Revenue ($ Millions)	IB Revenue ($ Millions)	Commission Revenue ($ Millions)
Merrill Lynch & Co., Inc.	231	18,608	2413	4657
Morgan Stanley, Dean Witter & Co.	199	32,415	2527	3280
Salomon Smith Barney Holdings, Inc.	139	21,250	3420	3845
Goldman Sachs & Co.	133	22,854	2572	4950
Bear Stearns & Co.	122	6891	833	1110

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