Analyst Conflicts and Research Quality

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Analyst Conflicts and Research Quality

Abstract

This paper examines whether the quality of stock analysts' forecasts is related to conflicts of interest from investment banking and brokerage. 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 investment banking, brokerage, and other businesses over the 1994-2003 period, we uncover two main findings. First, accuracy and bias in quarterly 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 frequency of revision 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 contrary to popular belief, conflicts from brokerage, rather than from investment banking, play an important role in shaping analysts' forecasting behavior.

Keywords: Stock analysts, Security analysts, Analyst conflicts, Corporate governance, Analyst forecasts, Wall Street research, Brokerage research, Conflicts of interest

JEL Classifications: G24, G28, G34, G38, K22, M41

Analyst Conflicts and Research Quality

1. Introduction

In April 2003, ten of the largest Wall Street firms reached a landmark settlement with the New York State Attorney General (NYSAG), the U.S. 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 analyst during the late 1990s stock market boom. Grubman, then an analyst with Salomon Smith Barney, raised his rating on AT&T stock in November 1999 from a 'hold' to a 'strong buy' in an apparent bid to curry favor with AT&T (see Gasparino (2002)).[1]

The settlement forces the securities firms to make structural changes in the production and dissemination of equity research (see Smith, Craig and Solomon (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 is earmarked for providing investors with stock research from independent research firms.

[1]Other instances of alleged conflicts of interest abound. A recent 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 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'.

The settlement is fundamentally grounded on the premise that analysts who are free from potential conflicts of interest do indeed produce superior, unbiased stock research. In this paper, we provide empirical evidence on whether the quality of analyst 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, is the magnitude of conflict with investment banking or brokerage related to the accuracy of analysts' quarterly EPS forecasts? Second, are conflicts related to the bias in quarterly forecasts? Third, how are conflicts related to the frequency of revision of quarterly forecasts? And finally, what is the relation between conflicts of interest and the relative optimism in long-term earnings growth (LTG) forecasts?

The answers to these questions are important not only to regulators and the academic profession, but also to a broad range of stock market participants. Both retail and institutional investors use analyst reports to form expectations about the 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 also found that analysts' earnings forecasts and stock recommendations have investment value (see, e.g., Givoly and Lakonishok (1979), Stickel (1991), Womack (1996), Barber, Lehavy, McNichols and Trueman (2001), Jegadeesh, Kim, Krische and Lee (2004), and Loh and Mian (2005)). 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 the empirical analysis, we have compiled a unique dataset that contains the revenue breakdown for analyst employers (most of which are private firms not subject to the usual disclosure requirements for publicly traded companies) into revenues from investment banking, 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 of over 170,000 quarterly EPS forecasts and over 38,000 LTG forecasts for about 7,400 U.S. public companies over the time period January 1994 to

March 2003. The forecasts are made by about 3,000 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. For instance, Lin and McNichols (1998), Michaely and Womack (1999) and others find that analysts employed by underwriters of security offerings tend to be more optimistic than other analysts about the prospects of the issuing company. Our paper contributes to this line of research in several ways. First, we examine the conflict of interest arising from investment banking in general, rather than solely from security offerings.[3] In addition to providing underwriting services to clients, an investment bank can sell them advisory services on issues of corporate control and restructuring. Second, our approach takes into account both actual as well as potential conflicts from IB activities. As long as an analyst's firm has an IB business, even if the firm does not *currently* do business with the company followed by an analyst, it might like to do so in the future. Third, as several prior studies have recognized, optimism among underwriter analysts is subject to the alternative interpretation that a company picks an underwriter whose analyst has a higher opinion of the stock to begin with. Because we examine research put forth by all analysts following a stock over time, the interpretation of our results is not subject to this ambiguity.

Fourth, 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 Section 2 below, IB and brokerage operations are two distinct sources of potential conflicts of interest, and they may influence analyst behavior in very different ways. Finally, our approach has the advantage of yielding sample sizes that are much larger than those used in prior research. Our paper complements Agrawal and Chen (2005), which uses a similar approach to analyze the relation between the magnitude of analyst conflicts and the nature and consequences of analysts' stock recommendations.

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[3]Concurrent research by Cowen, Groysberg and Healy (2003), Jacob, Rock and Weber (2003) and Clarke, Khorana, Patel and Rau (2004) also employs this approach. These studies use Nelson's Directory of Investment Research and the SDC Platinum database to classify analysts' employers. While these papers are similar in spirit to ours, our unique dataset on the revenue breakdown for analysts' employers allows us to measure the *magnitude* of the conflicts in addition to their presence. Furthermore, we analyze how

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 potential IB or brokerage conflicts, after controlling for forecast age, firm resources, analyst experience and analyst workloads. This result also holds for technology stocks and for forecasts made during the late 1990s stock market boom, sub-samples where analysts may have faced particularly severe conflicts. The result holds for analysts employed by publicly traded as well as private securities firms, and it is robust to the use of alternate measures of the conflict magnitude. Our analysis also indicates that the level of LTG forecasts and the frequency of revision of quarterly EPS forecasts are both positively related to the importance of brokerage conflicts. Further investigation of our result on forecast frequency reveals that the more severe are brokerage conflicts, the less that forecast revisions can be explained solely as attempts to provide investors with timely and accurate information. Trade-generation motives appear to partly drive forecast revisions when brokerage conflicts are severe.

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 long-term (EPS growth) forecasts. This difference may be because analysts' concerns about loss of reputation may be more serious with short-term forecasts than with long-term forecasts. Second, despite obvious instances of distortion that have been portrayed in the media, we find no systematic relationship between the magnitude of investment banking conflicts and several aspects of analysts' forecasting behavior. However, brokerage conflicts appear to play a more important role in shaping analysts' forecasting behavior than has been previously recognized.

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

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conflicts faced by analysts are related to the revision frequency of quarterly EPS forecasts, an issue not addressed by any other study.

results for two interesting sub-samples: technology 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 relative optimism in long-term earnings growth projections. Section 2.1 deals with investment banking conflicts and section 2.2 deals with brokerage conflicts.

2.1 Investment banking conflicts

The most widely discussed type of analyst conflict arises from the fact that securities firms may seek to win lucrative underwriting business by issuing optimistic research about current or potential clients.[4] Several academic studies have reported evidence of analyst optimism within the context of existing underwriting relationships. For example, Dugar and Nathan (1995) and Lin and McNichols (1998) find that analysts employed by underwriters of seasoned equity offerings issue more favorable earnings forecasts and stock recommendations about clients than do non-underwriter analysts. Dechow, Hutton, and Sloan (2000) document a positive bias in underwriter analysts' long-term growth forecasts for firms conducting seasoned equity offerings. Michaely and Womack (1999) find that underwriter analysts in initial public offerings generally issue more optimistic recommendations about client firms than do non-underwriter analysts, but that the firms favored by underwriter analysts exhibit particularly poor long-run stock performance. And O'Brien, McNichols and Lin (2005) find that underwriter analysts in equity offerings are slower than other analysts to downgrade stocks, but are faster to upgrade them.

Securities firms seek not only to maintain the goodwill of existing investment banking clients, but also to attract new corporate clients. Corporate managers may choose to award underwriting or merger advisory deals to securities firms that issue consistently

[4]For a recent empirical analysis of whether analyst optimism helps generate underwriting deals, see Ljungqvist, Marston and Wilhelm (2005).

optimistic earnings forecasts. To the extent that this is true, EPS forecasts of analysts subject to pressure from investment banking should exhibit a positive bias relative to forecasts of analysts at independent firms. Likewise, the long-term (three to five year) earnings growth estimates of analysts at investment banking firms should be rosier than the growth projections of independent analysts.

Alternatively, pressure from investment banking operations may lead to a *pessimistic* bias in analysts' 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 may serve as a rule of thumb by which boards of directors and investors evaluate managers (see, e.g., Degeorge, Patel, and Zeckhauser (1999) and Farrell and Whidbee (2003)). Indeed, Bartov, Givoly, and Hayn (2002) find that companies that exceed the threshold set by analyst estimates subsequently experience higher abnormal stock returns. 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 investment banking 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 lead to greater accuracy or less bias among analysts working at large investment banking firms. 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 greater resources and support for conducting research (Clement (1999)) or access to superior information from underwriting and due diligence (Michaely and Womack (1999)). Second, firms with large investment banking 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, and such firms are more likely than smaller, regional firms to have significant investment banking operations.

Finally, reputation concerns can reduce analysts' response to IB conflicts. Markets can punish misbehaving analysts by hurting their career prospects. To the extent that analysts want to avoid the risk of tarnishing their reputations, they will be less

inclined to knowingly issue biased and inaccurate forecasts. Thus, the effect of investment banking 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 could face direct or indirect incentives to use their research to generate trading commissions.[5] For example, an analyst may be able to increase trading volume by issuing optimistic forecasts.[6] A new earnings forecast that is particularly positive should lead to trading from both new investors and current stockholders, provided that investors ascribe at least some information content to the forecast. On the other hand, a negative forecast should generate trading from a narrower set of investors, as generally only existing stockholders will trade in response to the forecast.[7]

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, Atiase, and Gift (1991)) and to significantly affect stock prices apart from earnings news, dividends, or other corporate announcements (see, e.g., Stickel (1991)). This positive relation between the frequency of forecast revision and trading volume can be beneficial to investors. For example, if producing forecasts and forecast revisions are costly activities, then analysts who are compensated for commission revenue may be more willing than independent analysts to issue timely

[5]Some 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).

[6]Carleton, Chen and Steiner (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.

[7]There are numerous regulations in the United States that increase the cost of selling shares short (see Dechow, Hutton, Meulbroek and Sloan (2001)). Furthermore, traditional mutual funds that qualify as SEC-registered investment vehicles 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 ten percent of the annual New York Stock Exchange trading volume (see NYSE (2002)).

revisions that reflect changing expectations about earnings. Indeed, previous work has established a link between analysts' forecasting frequency and their ultimate accuracy (see, e.g., Stickel (1992) and 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.[8] If churning incentives are important, then one would expect that, relative to independent analysts' forecasts, conflicted analysts' forecasts would be revised more frequently and more substantially, and yet would not necessarily end up being more accurate.

As with investment banking conflicts, concerns about loss of reputation can limit abusive 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 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

[8]Irvine (2004), using transactions data from the Toronto Stock Exchange, finds that a brokerage firm's market share of trading in a stock tends to increase when its analyst issues a forecast away from the consensus. But simply increasing forecast bias does not increase market share.

contains 1,257 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 1,098 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 1,098 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 U.S. 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 components of broker-dealers are key data items used in this study, we exclude 454 firms for which no revenue data are 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.[9]

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. Among the private firms for which we have balance sheet information, firms that do and do not opt for confidential treatment exhibit significant differences in financial characteristics during 2002 (see the Appendix and Table A.1). In additional untabulated analysis, we examine the importance of this potential selection bias for our results by conducting 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 sub-sample because all publicly-traded firms are required to disclose their income statements in annual 10-K filings. The similarity in results for the two groups of firms suggests that selection bias is likely not a serious issue for our purposes.

[9]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 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 typical (median) securities firm is quite small, with total revenue of only $3.25 million. The majority of firms have no investment banking 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 investment banking 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 investment banking 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 .004 (.488) and mean of .112 (.506). For the sub-sample of publicly-traded securities firms, the corresponding range for the IB (brokerage) revenue fraction is from 0 (.005) to .913 (.999) with a median of .114 (.362) and mean of .137 (.393). Thus, compared to private securities firms, publicly-traded firms derive a substantially greater proportion of their revenue from IB.

We obtain forecasts and reported earnings per share (EPS) numbers from the I/B/E/S U.S. Detail History File for the time period from January 1, 1994 to June 30, 2003. All EPS forecast 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 twelve 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 pennies 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 pennies on a $50 stock for both forecast periods. For long-term earnings growth projections, the median forecast level is strikingly high, about 16% per year.[10] 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; her median

[10] 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.

general forecasting experience is about three years.[11] 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[12] industry groups.

Appendix Table A.2 lists, for fiscal year 2002, the largest employers of analysts as well as the largest employers with either no investment banking 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 analysts and has total revenue of about $62 million, all of which consists of brokerage commissions.[13]

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 investment banking, $4.7 billion from brokerage commissions, and the rest from other businesses.

4. Empirical results

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

[11]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.

[12]Sector / Industry / Group code.

[13]Commission revenue slightly exceeds total revenue. The latter includes a loss from the firm's trading activities.

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 investment banking (or brokerage) business. We define a broker-dealer firm to have significant (insignificant) investment banking business if, at the end of the preceding fiscal year, its investment banking 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 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 include variables that have been found in

prior research (e.g., Mikhail, Walther and Willis (1997), Clement (1999), and Jacob, Lys and Neale (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:

$$(1) \quad NAFE_{ijt} = b_0 + b_1\, IB_{it} + b_2\, COM_{it} + b_3\, AGE_{ijt} + b_4\, SIZE_{it} + b_5\, CEXP_{ijt} + b_6\, GEXP_{it} + b_7\, NCOS_{it} + b_8\, NIND_{it} + b_9\, PUBLIC_{it} + e_{ijt},$$

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 section 3,

IB (or COM) = investment banking (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 equation (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 variables. We use three alternative econometric

approaches to estimate equation (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.[14] 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. 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 (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.[15] 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.[16] 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

[14]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.

[15]The correlation between IB and COM is -.17. Throughout the paper, results are similar when we include IB and COM variables one at a time in the regressions.

[16]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.

evidence that forecast inaccuracy is different for analysts employed by publicly-traded versus private securities firms.

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 equation (1). Here too, the unit of observation in the pooled OLS and fixed effects regressions is an analyst-company-year-quarter. 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, Foster and Noreen (1985) and Richardson, Teoh and Wysocki (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. Long-term earnings growth (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 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 equation (1), except that the forecast AGE variable is no longer relevant and is 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%[17]. 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 is an analyst-company-year-quarter. All three specifications include industry and year-quarter dummies.[18] The explanatory variables are the same as in equation (1), except that the IB and AGE variables are excluded

[17]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.

[18]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.

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 .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 section 2.2, the positive relation we find between COM and forecast revision frequency in section 4.4 above is consistent with two distinct motives. On the 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 sections 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 the Table 8 regressions of forecast revision frequency. The more uncertain are 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 .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,[19] denoted $CHURN_1$ and $CHURN_2$, and estimate the following regression:

$$(2) \qquad CHURN_{ijt} = bo + b_1\, COM_{it} + b_2\, SIZE_{it} + e_{ijt},$$

where the subscripts denote analyst i following company j for year-quarter t, COM and SIZE are as defined as in section 4.1 above, and the churning measure is defined as follows:

$CHURN = CHURN_1$ or $CHURN_2$,

$CHURN_1$ = Mean absolute forecast revision = $\sum_{k=2}^{n} |d_k - d_{k-1}| / (n-1)$,

[19]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.

$CHURN_2$ = Mean squared forecast revision = $\sum_{k=2}^{n} (d_k - d_{k-1})^2 / (n-1)$,

$d_k = F_k / S$,

F_k = kth 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 6-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 forecasts. This implies that the coefficient b_1 in equation (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 equation (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 absolute magnitude of successive changes in an analyst's forecasts appears to be positively related to the strength of brokerage conflicts. This evidence is consistent with the idea that analysts employed by firms where brokerage business is more important issue more frequent forecast updates 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:

(3) $\Delta NAFE_{ijt} = b_0 + b_1\ BOLDNESS_{ijt} * HCOM_{it} + b_2\ BOLDNESS_{ijt} * LCOM_{it} + b_3\ NDAYS_{ijt} + e_{ijt}$,

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

$\Delta NAFE_{ijt} = NAFE_{ijt} - NAFE_{ij,t-1}$,

$BOLDNESS_i = |F_i - F| / S$,

F_i = Forecast of analyst i for a given company-year-quarter,

F = Consensus forecast for the company-year-quarter,

S= Stock price twelve months before quarter-end,

$HCOM_i$ = 1, if analyst i works for an employer with high (above-median) COM,

= 0 otherwise,

$LCOM_i = 1 - HCOM_i$,

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 (more) negative for analysts who face higher (lower) degrees of brokerage conflict.

Our estimation of equation (3) indicates that $\hat{b}_1$ = -.13 and $\hat{b}_2$ = -.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 .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 equation (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 section 6.1 and the results for the late 1990s versus other time periods in section 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 or bias in an analyst's quarterly earnings forecasts and the importance to her 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 her employer in each sector, with no significant difference in the coefficient estimates. But the level of analysts' long-term growth 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 1995-99; 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 investment banking 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 conclusions

The landmark settlement that prominent Wall Street firms reached with regulators in April 2003 mandates sweeping changes in the production and dissemination of sell-side analyst research. Among its key provisions, the settlement requires securities firms to create and maintain greater separation between equity research and investment banking 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 investment banking or brokerage. A unique dataset detailing securities firms' revenues from investment banking, brokerage, and other businesses allows us to

examine the effects of analyst conflicts on four aspects of forecasts: accuracy and bias in quarterly earnings forecasts, optimism in long-term growth (LTG) forecasts, and the frequency of quarterly forecast revisions.

Our investigation reveals that the bias and accuracy of quarterly EPS forecasts do not appear to be systematically related to the importance of investment banking or brokerage business to analysts' employers. This result also holds for forecasts made for companies within the technology sector as well as those 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 true for both 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 on forecast revision frequency. The results of these tests suggest that analysts' trade generation incentives can indeed impair the quality of stock research. It follows that distortions in analyst research are unlikely to be completely eliminated by the April 2003 global settlement, which focuses on investment banking conflicts. The precise nature of trade generation incentives, how they impact analyst behavior, and how they might be mitigated are all interesting 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, causing irreparable damage to 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

Financial characteristics of in-sample versus out-of-sample securities firms

Table A.1 compares mean and median values of firm size, financial leverage and liquidity of private broker-dealer firms that disclosed annual revenue information in their x-17a-5 filings with the SEC (labeled 'sample firms' in the table) versus private broker-dealer firms that did not (labeled 'other firms'). The table also provides financial characteristics for publicly traded broker-dealers that made annual 10-K filings with the SEC. Our sample consists of all private securities firms that disclose the breakdown of their annual revenues and all publicly traded securities firms. All financial information is for fiscal years ending in 2002. The table includes all broker-dealer firms in the I/B/E/S Broker Translation File for which a form x-17a-5 or form 10-K was available. The table reports p-values for t-tests and Wilcoxon rank-sum tests for differences between private firms in the sample versus other private firms.

Among private firms, the in-sample firms are smaller than firms that do not disclose their income statements. The median total assets of the two groups are about $0.9 million and $9.4 million, respectively; their median book equity is $0.6 million and $4.9 million, respectively. The median financial leverage of both groups of firms is zero; the mean leverage is slightly lower for the sample firms than for the non-sample firms. The median in-sample firm has about 23% of its assets in cash, compared to 11% for the median out-of-sample firm. All these differences are statistically significant at the .05 level.

The publicly traded securities firms are clearly much larger than either the in-sample or out-of-sample private firms. The median value of public firms' total assets is about $727 million and their median book equity is about $237 million. They also have larger leverage ratios and lower cash positions compared to private firms in either group.

Table 1
Sample Characteristics

This table provides descriptive statistics on broker-dealers, analysts, and forecasts. The sample includes I/B/E/S quarterly earnings and long-term earnings growth (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 investment banking or brokerage businesses. N is the number of firm-years. Panel C reports characteristics of long-term growth (LTG) forecasts and quarterly EPS forecasts over the entire sample period. Bias is computed as (actual EPS-forecast EPS) divided by the stock price twelve 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 the forecast date and the 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.

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: Investment Banking 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								
Investment banking fraction	972	0	0	0.004	0.136	1	0.112	0.194
Brokerage commission	972	0	0.207	0.488	0.853	1	0.506	0.341
Public broker-dealers								
Investment banking fraction	227	0	0.069	0.114	0.154	0.913	0.137	0.137
Brokerage commission	227	0.005	0.160	0.362	0.494	0.999	0.393	0.276

Table 1 (cont.)

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.
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	9,387	Analyst-year
Number of analysts employed by firm	76.55	61	9,387	Analyst-year
Number of companies covered	10.19	9	9,387	Analyst-year
Number of 4-digit I/B/E/S SIG industry groups covered	2.39	2	9,378	Analyst-year

Table 2
Forecast Accuracy of Analysts Employed by Firms with Versus without Significant Investment Banking or Brokerage Business

This table presents univariate comparisons of quarterly EPS forecast inaccuracy between different groups of analysts classified according to whether their employer has significant investment banking 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) investment banking business in a given calendar year if its investment banking 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 U.S. 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 U.S. Securities and Exchange Commission. Forecasts are matched with annual broker-dealer financial data corresponding to the latest fiscal year preceding the date of the forecast.

Type of Firm	A. One-month Forecast Period			B. Three-month Forecast Period		
	N	**Mean**	**Median**	***N***	**Mean**	**Median**
1. Firms with no significant IB business	3683	0.0029	0.0010	16789	0.0032	0.0010
2. Firms with significant IB business	3683	0.0028	0.0010	16789	0.0031	0.0010
p-value of t-test/signed-rank test (1 vs. 2)		0.433	0.059		0.132	0.160
3. Firms with no significant brokerage business	3370	0.0026	0.0009	13982	0.0029	0.0009
4. Firms with significant brokerage business	3370	0.0029	0.0010	13982	0.0031	0.0010
p-value of t-test/signed-rank test (3 vs. 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 vs. 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 vs. 8)		0.818	0.581		0.024	0.084

Table 3
Panel Regression Analysis of Quarterly Earnings Forecast Accuracy

This table reports coefficients 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 |reported EPS – forecast EPS| divided by the stock price twelve 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. The pooled OLS regressions include industry and calendar-quarter dummies (not reported). (2) reports 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 U.S. Securities and Exchange Commission. 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.

	Pooled OLS (1)		Fama-MacBeth (2)		Company-Quarter Fixed Effects (3)	
Panel A: One-Month Forecast Period						
Constant	-0.0083 (-6.99)[a]	-0.0083 (-6.99)[a]	-0.0040 (-2.25)[b]	-0.0049 (-2.44)[b]	0.0030 (8.82)[a]	0.0030 (8.82)[a]
Investment banking revenue as fraction of total revenue	-0.0009 (-0.67)	-0.00089 (-0.66)	-0.0015 (-1.10)	0.0012 (0.52)	-0.00020 (-0.52)	-0.00020 (-0.52)
Commission revenue as fraction of total revenue	0.00036 (0.76)	0.00036 (0.75)	0.00076 (1.82)	-0.00018 (-0.33)	0.00014 (0.69)	0.00014 (0.70)
Forecast age	0.00009 (9.15)[a]	0.00009 (9.16)[a]	0.00009 (8.07)[a]	0.0001 (8.02)[a]	0.00003 (7.18)[a]	0.00003 (7.18)[a]
Ln (1+Number of analysts employed by brokerage)	0.00015 (1.51)	0.00011 (0.89)	0.0002 (2.00)[b]	0.00015 (1.19)	-0.00012 (-2.41)[b]	-0.00013 (-2.19)[b]
Company-specific forecasting experience * 10^{-3}	0.1799 (6.31)[a]	0.1804 (6.31)[a]	0.1750 (5.14)[a]	0.1750 (5.23)[a]	-0.0250 (-1.81)	-0.0248 (-1.81)
General forecasting experience * 10^{-3}	-0.0552 (-2.27)[b]	-0.0558 (-2.28)[b]	-0.0276 (-1.36)	-0.02667 (-1.34)	0.034 (3.27)[a]	0.0341 (3.27)[a]
Number of companies followed * 10^{-3}	0.00075 (-0.07)	0.00067 (-0.06)	0.0075 (0.51)	0.0086 (0.58)	-0.0041 (-0.82)	-0.0041 (-0.83)
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	45374	45374	45267	45267	45374	45374
Number of Groups					27704	27704
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

Table 3 (cont.)

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]
Investment banking 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)
Number of Observations	143477	143477	143318	143318	143477	143477
Number of Groups					61996	61996
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.

Table 4
Forecast Bias of Analysts Employed by Firms with Versus without Significant Investment Banking or Brokerage Business

This table presents univariate comparisons of quarterly EPS forecast bias between different groups of analysts classified according to whether their employer has significant investment banking 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 twelve months before quarter end. Forecasts are drawn from the January 1994-June 2003 period. A broker-dealer is defined to have significant (insignificant) investment banking business in a given calendar year if its investment banking 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 U.S. 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 U.S. Securities and Exchange Commission. Forecasts are matched with annual broker-dealer financial data corresponding to the latest fiscal year preceding the date of the forecast.

Type of Firm	A. One-month Forecast Period			B. Three-month Forecast Period		
	N	Mean	Median	*N*	Mean	Median
1. Firms with no significant IB business	3683	0.00007	0.0002	16789	$-5.6*10^{-6}$	0.00026
2. Firms with significant IB business	3683	0.00011	0.0003	16789	0.00003	0.00029
p-value of t-test/signed-rank test (1 vs. 2)		0.747	0.028		0.493	0.0001
3. Firms with no significant brokerage business	3370	0.00003	0.00025	13982	0.00008	0.00027
4. Firms with significant brokerage business	3370	-0.00013	0.00020	13982	-0.00006	0.00025
p-value of t-test/signed-rank test (3 vs. 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 vs. 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 vs. 8)		0.620	0.934		0.447	0.008

Table 5
Panel Regression Analysis of Quarterly Earnings Forecast Bias

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 twelve 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 (continuous) measures of 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.

	Pooled OLS (1)		Fama-MacBeth (2)		Company-Quarter Fixed Effects (3)	
Panel A: One-Month Forecast Period						
Constant	0.0045 (3.55)[a]	0.0045 (3.54)[a]	0.0050 (2.79)[a]	0.0048 (2.59)[a]	0.00086 (2.29)[b]	0.00085 (2.27)[b]
Investment banking revenue as fraction of total revenue	0.00088 (0.64)	0.00087 (0.63)	-0.00027 (-0.16)	0.00026 (0.14)	0.00019 (0.47))	0.00019 (0.47)
Commission revenue as fraction of total revenue	-0.00017 (-0.34)	-0.00016 (-0.32)	-0.00097 (-1.71)	-0.0006 (-1.09)	-0.00019 (-0.88)	-0.0002 (-0.92)
Forecast age	-0.00006 (-5.67)[a]	-0.00006 (-5.68)[a]	-0.00006 (-4.52)[a]	-0.00006 (-4.51)[a]	-0.00003 (-5.76)[a]	-0.00003 (-5.78)[a]
Ln (1 + Number of analysts employed by brokerage)	0.00015 (1.49)	0.00023 (1.93)	0.00009 (0.65)	0.00025 (1.52)	0.00006 (1.16)	0.00009 (1.48)
Company-specific forecasting experience * 10^{-3}	-0.1149 (-3.86)[a]	-0.1158 (-3.89)[a]	-0.1193 (-3.18)[a]	-0.1187 (-3.18)[a]	-0.0073 (-0.49)	-0.0075 (-0.49)
General forecasting experience * 10^{-3}	0.0448 (1.76)	0.0458 (1.80)	0.0391 (1.49)	0.0381 (1.48)	0.026 (2.27)[b]	0.0262 (2.28)[b]
Number of companies followed * 10^{-3}	-0.0125 (-1.10)	-0.0126 (-1.11)	-0.0211 (-1.37)	-0.0219 (-1.46)	-0.0038 (-0.70)	-0.0037 (-0.68)
Number of industry groups followed * 10^{-3}	-0.060 (-0.90)	-0.0621 (-0.93)	-0.0492 (-0.67)	-0.0474 (-0.65)	-0.0737 (-2.34)[b]	-0.0754 (-2.39)[b]
Ln (Market capitalization of company)	0.00024 (3.48)[a]	0.00024 (3.48)[a]	0.00028 (3.72)[a]	0.00028 (3.71)[a]		
Public broker-dealer dummy		-0.0003 (-0.97)		-0.00026 (-0.79)		-0.00013 (-0.95)
Number of Observations	45374	45374	45267	45267	45374	45374
Number of Groups					27704	27704
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 (cont.)

Panel B: Three-Month Forecast Period						
Constant	0.0025 (3.87)[a]	0.0025 (3.86)[a]	0.0021 (2.63)[a]	0.0030 (3.28)[a]	0.0002 (1.19)	0.0002 (1.22)
Investment banking revenue as fraction of total revenue	-0.00066 (-1.18)	-0.00065 (-1.17)	-0.0050 (-1.08)	-0.0065 (-1.48)	0.00016 (0.78)	0.00016 (0.78)
Commission revenue as fraction of total revenue	-0.00012 (-0.43)	-0.00012 (-0.44)	-0.00054 (-1.13)	-0.00024 (-0.75)	0.00002 (0.21)	0.00003 (0.24)
Forecast age	-0.00003 (-9.39)[a]	-0.00003 (-9.39)[a]	-0.00003 (-6.04)[a]	-0.00003 (-6.01)[a]	-0.00001 (-14.88)[a]	-0.00001 (-14.89)[a]
Ln (1+Number of analysts employed by brokerage)	0.00014 (2.33)[b]	0.00017 (2.39)[b]	0.00036 (2.31)[b]	0.00042 (2.26)[b]	0.00009 (3.36)[a]	0.00008 (2.55)[b]
Company-specific forecasting experience * 10^{-3}	-0.0606 (-2.50)[b]	-0.0610 (-2.50)[b]	-0.0778 (-3.47)[a]	-0.0769 (-3.42)[a]	0.012 (1.47)	0.0121 (1.49)
General forecasting experience * 10^{-3}	-0.0126 (-0.73)	-0.0122 (-0.70)	-0.0100 (-0.70)	-0.0097 (-0.67)	0.00343 (0.59)	0.0034 (0.58)
Number of companies followed * 10^{-3}	0.0245 (4.07)[a]	0.0245 (4.08)[a]	0.0129 (1.36)	0.0121 (1.27)	-0.0019 (-0.69)	-0.0195 (-0.70)
Number of industry groups followed * 10^{-3}	-0.0920 (-2.46)[b]	-0.0928 (-2.49)[b]	-0.0808 (-1.62)	-0.0779 (-1.56)	-0.0414 (-2.55)[b]	-0.041 (-2.53)[b]
Ln (Market capitalization of company)	0.00035 (7.68)[a]	0.00035 (7.68)[a]	0.00043 (5.99)[a]	0.00043 (6.01)[a]		
Public broker-dealer dummy		-0.00011 (-0.61)		-0.0011 (-2.72)[a]		-0.00004 (0.58)
Number of Observations	143477	143477	143318	143318	143477	143477
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.

Table 6
Long-term Earnings Growth (LTG) Forecasts of Analysts Employed by Firms with Versus without Significant Investment Banking or Brokerage Business

Univariate comparisons of long-term (3 to 5 years) growth forecasts between different groups of analysts classified according to whether their employer has significant investment banking or brokerage business. The sample period is from January 1994 through June 2003. A broker-dealer is defined to have significant (insignificant) investment banking business in a given calendar year if its investment banking 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 U.S. 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 U.S. Securities and Exchange Commission. Forecasts are matched with annual broker-dealer financial data corresponding to the latest fiscal year preceding the date of the forecast.

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 vs. 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 vs. 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 vs. 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 vs. 8)		0.033	0.016

Table 7
Analysis of Long-Term Earnings Growth Forecasts

This table reports coefficients from regressions explaining the level of long-term earnings growth (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 U.S. Securities and Exchange Commission. 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. 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.

	Fama-MacBeth (1)		Company-Quarter Fixed Effects (2)	
Constant	20.17 (3.16)[a]	17.33 (2.37)[b]	21.54 (28.87)[a]	21.58 (28.64)[a]
Investment banking revenue as fraction of total revenue	3.53 (0.29)	8.86 (0.61)	0.151 (0.14)	0.158 (0.15)
Commission revenue as fraction of total revenue	6.68 (0.64)	-2.16 (-0.68)	1.27 (2.39)[b]	1.257 (2.37)[b]
Ln (1+Number of analysts employed by brokerage)	-0.498 (-0.65)	-0.22 (-0.27)	-0.516 (-3.61)[a]	-0.543 (-3.28)[a]
Company-specific forecasting experience	-0.649 (-17.03)[a]	-0.65 (-16.90)[a]	0.026 (0.78)	0.026 (0.79)
General forecasting experience	-0.003 (-0.08)	-0.005 (-0.15)	-0.005 (-0.26)	-0.005 (-0.27)
Number of companies followed	-0.032 (-2.05)[b]	-0.034 (-2.11)[b]	-0.007 (-0.73)	-0.007 (-0.74)
Number of industry groups followed	0.185 (3.03)[a]	0.185 (2.97)[a]	0.035 (0.54)	0.035 (0.54)
Public broker-dealer dummy		3.459 (1.05)		0.090 (0.32)
Number of Observations	35258	35258	35319	35319
Number of Groups			26870	26870
R^2	0.008	0.008	0.007	0.007

[a,b] denote statistical significance in 2-tailed tests at the 1% and 5% levels, respectively.

Table 8
Analysis of Quarterly Earnings Forecast Frequency

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. The dependent variable in the OLS and Poisson regressions in (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 (2) is an indicator variable equal to unity if an analyst issued more than one forecast during the three-month forecasting period and equal to zero otherwise. 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 U.S. Securities and Exchange Commission 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 preceding 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.

	OLS Specification (1)		Logistic Specification (2)		Poisson Specification (3)	
Constant	1.4321 (17.29)[a]	1.4324 (17.29)[a]	-0.9397 (-3.38)[a]	-2.2965 (-6.37)[a]	0.3521 (5.94)[a]	0.0784 (1.32)
Commission revenue as fraction of total revenue	0.0606 (6.75)[a]	0.0607 (6.77)[a]	0.2008 (5.49)[a]	0.1995 (5.46)[a]	0.0465 (6.81)[a]	0.0467 (6.84)[a]
Ln (1+Number of analysts employed by brokerage)	0.0140 (6.67)[a]	0.0121 (4.79)[a]	0.0838 (9.56)[a]	0.0895 (8.56)[a]	0.0114 (7.11)[a]	0.0101 (5.27)[a]
Company-specific forecasting experience	0.0088 (12.51)[a]	0.0088 (12.53)[a]	0.0265 (10.75)[a]	0.0265 (10.71)[a]	0.0062 (12.12)[a]	0.0062 (12.14)[a]
General forecasting experience	-0.0015 (-3.24)[a]	-0.0016 (-3.29)[a]	-0.0049 (-2.63)[a]	-0.0049 (-2.59)[a]	-0.0011 (-3.16)[a]	-0.0011 (-3.20)[a]
Number of companies followed	0.0011 (6.39)[a]	0.0011 (6.39)[a]	0.0042 (5.70)[a]	0.0042 (5.70)[a]	0.0009 (6.64)[a]	0.0009 (6.64)[a]
Number of industry groups followed	-0.0080 (-7.91)[a]	-0.0079 (-7.86)[a]	-0.0268 (-6.26)[a]	-0.0270 (-6.30)[a]	-0.0060 (-7.74)[a]	-0.0059 (-7.69)[a]
Ln (Market capitalization of company)	0.0291 (30.67)[a]	0.0291 (30.65)[a]	0.1071 (28.75)[a]	0.1072 (28.76)[a]	0.0222 (31.15)[a]	0.0221 (31.12)[a]
Public broker-dealer dummy		0.0077 (1.46)		-0.0230 (-1.00)		0.0052 (1.27)
Number of Observations	143474	143474	143474	143474	143474	143474
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 2-tailed tests at the 1% and 5% levels, respectively.

Table A.1: Financial Characteristics of In-Sample vs. Out-of-Sample Securities Firms, 2002

This table compares selected financial characteristics of private (i.e., non-publicly-traded**)** broker-dealer firms with SEC x-17a-5 filings that disclosed annual revenue information ('sample firms') versus other private x-17a-5 filers that did not disclose it ('other firms'). The table also provides financial characteristics for publicly traded broker-dealers that made annual 10-K filings with the SEC during 2002; all public firms are also included in our overall sample. All financial information is for fiscal years ending in 2002. The table includes all broker-dealer firms in the I/B/E/S broker translation file for which a 2002 form x-17a-5 or form 10-K was available. P-values are reported for t-tests and for Wilcoxon rank-sum tests for differences between sample firms and other firms.

	Private Firms (non-10-K filers)						Publicly Traded Firms (10-K Filers)	
	Mean			Median			Mean	Median
	Sample Firms (N=126)	Other Firms (N=176)	p-value	Sample Firms (N=126)	Other Firms (N=176)	p-value	(N=25)	(N=25)
Firm Size								
Total Assets ($ millions)	111.52	3205.13	0.026	0.87	9.39	0.000	83319.06	406.19
Book Equity ($ millions)	13.81	92.01	0.032	0.61	4.89	0.000	2940.83	79.99
Financial Leverage								
LT Debt/ Total Assets	0.036	0.087	0.033	0.000	0.000	0.001	0.157	0.011
(LT Debt + ST Debt)/ Total Assets	0.047	0.109	0.013	0.000	0.000	0.001	0.207	0.079
Liquidity								
Cash and Equivalents/ Total Assets	0.336	0.563	0.525	0.23	0.11	0.013	0.134	0.035

Table A.2: Firms Employing 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 ($m)
Merrill Lynch & Co., Inc.	231	18,608	2,413	4,657
Morgan Stanley, Dean Witter & Co.	199	32,415	2,527	3,280
Salomon Smith Barney Holdings, Inc.	139	21,250	3,420	3,845
Goldman Sachs & Co.	133	22,854	2,572	4,950
Bear Stearns & Co.	122	6,891	833	1,110