

DO SECURITY ANALYSTS SPEAK IN TWO TONGUES?*

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Why do security analysts issue overly positive recommendations? We propose a novel empirical strategy to assess the relative importance of the leading explanations: strategic distortion, which reflects incentives to trigger small-investor purchases and please management, and non-strategic distortion, which reflects genuine over-optimism, due to self-selection or credulity. We exploit the concurrent issuance of recommendations and earnings forecasts by the same analyst to distinguish those motivations. While non-strategic distorters express their positive view both in recommendations and in forecasts, strategic distorters issue overly positive recommendations but slightly more negative (“beatable”) forecasts. We find that affiliated analysts who have the most positive recommendations outstanding make the most negative forecasts. The same does not hold for unaffiliated analysts. Affiliated analysts are also more likely to distort forecasts downwards just before earnings announcements, allowing management to beat the forecast. Our findings indicate widespread strategic distortion, though the heterogeneity across analysts is large. We show that strategic distortion is persistent within individual analysts, with potential forensic implications.

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A large body of research has examined upward distortions of analyst recommendations.¹ The explanations for these distortions can be grouped into two types: strategic and non-strategic distortion.² Strategic distortion reflects misaligned incentives: Analysts consciously bias recommendations upwards in an effort to please company management, generate corporate finance business, and induce investors to purchase stock (Michaely and Womack [1999]). For example, management often calls up analysts to complain about low ratings, and used to “freeze out” analysts who do not give positive recommendations (Francis, Hanna and Philbrick [1997], Chen and Matsumoto [2006]). Similarly, buy-side clients push sell-side analysts to maintain positive recommendations on stocks they hold.³ Non-strategic distortion, instead, means that analysts genuinely have too positive expectations, e. g., due to self-selection into the stocks they choose to cover and which they view too favorably, or simply due to credulity (see McNichols and O’Brien [1997], Teoh and Wong [2002]). As a result, their recommendation might be too positive, akin to the winner’s curse: whoever receives the most positive signal should infer that the signal is likely too positive – but may fail to do so.

We still know little about the relative importance of those motivations. In this paper, we propose a novel empirical approach to fill this gap. We exploit the fact that analysts provide investment advice using both earnings forecasts and recommendations.⁴ We argue that investors’ ability to process the information depends on the mode of communication (Hirshleifer and Teoh [2003]) and on their sophistication: large institutional investors are able to filter out the relevant information regardless of the format while small individual investors are not. The systematic differences are important since analysts have fewer incentives to distort strategically when facing institutional investors (see, e.g., Ljungqvist et al. [2005]). The basic idea of our empirical identification is that, if the ability to process information varies by audience and by mode of communication, the optimal strategic distortion varies as well while non-strategic distortion does not.

¹ See Michaely and Womack [2005] for an excellent recent review of the recommendations literature.

² Lin and McNichols [1998] use the terminology “strategic and non-strategic bias” to distinguish whether analyst distortion is aimed at being selected as an underwriter or not. Our notion is broader: “strategic” refers to any incentive misalignment, e. g., to increase small-investor trades or cater to management. Kothari [2001] uses “incentives-based versus cognitive” to capture the same distinction in the context of forecasts.

³ Boni and Womack [2002] cite several press reports and the testimony of the (then) acting SEC chairman Laura Unger to the House Subcommittee on July 31, 2001.

⁴ See Ertimur, Sunder and Sunder [2007] and Loh and Mian [2006] for related approaches, assessing analysts’ skill in translating accurate earnings forecasts into profitable recommendations.

The empirical strategy consists of four steps. The first two are auxiliary steps towards our primary contribution, in the last two steps, of showing that a single analyst can “speak in two tongues” with recommendations and forecasts and that strategic behavior is persistent over time. First, using IBES data, we replicate prior studies in comparing the average degree of distortion in recommendations and in annual earnings forecasts.⁵ Consistent with Lin and McNichols [1998] and Michaely and Womack [1999], we find that recommendations are significantly more positive if analysts are affiliated with an underwriter of the covered firm than if they are unaffiliated. However, we also find that affiliated earnings forecasts are significantly more *negative* than unaffiliated forecasts, both in absolute magnitudes and relative to the respective consensus.⁶ Similarly, if we compare recommendations to the consensus, recommendation optimism is significantly higher for affiliated than for unaffiliated analysts, while earnings forecast optimism relative to the consensus is significantly lower for affiliated than for unaffiliated analysts.

The higher distortion of affiliated recommendations does not allow to distinguish between strategic and non-strategic distortion since both can be stronger among affiliated analysts – strategic distortion because corporate finance departments might pressure their analysts to support underwriting business with positive recommendations,⁷ and non-strategic distortion because analysts are affected by the positive view implicit in their investment bank’s decision to finance a company or, vice versa, because the analyst’s genuine overoptimism encouraged the corporate finance division to seek out the underwriting business in the first place. However, the discrepancy between higher upward distortion of recommendations and more downward distortion of forecasts does allow a distinction: In the second step, we link the differences in distortive behavior to different investors’ information processing and to different management pressures. Using the New York Stock Exchange Trades and Quotations (TAQ) database (1993-2002), we first confirm the findings of previous literature (Iskoz [2002], Malmendier and Shanthikumar [2007], Mikhail, Walther, and Willis [2007]) that both small and large investors react

⁵ We also replicate all results using quarterly earnings forecasts and long-term growth forecasts. The data and all results are described in detail in Online Appendix A.

⁶ Lin and McNichols [1998] find no difference between SEO-affiliated and unaffiliated analysts for earnings forecasts made just before or just after SEO. We focus on a longer post-IPO/SEO window.

⁷ See Bradley, Jordan, and Ritter [2003]. Ljungqvist, Marston and Wilhelm [2006] show that while analysts respond to these incentives, they fail to win underwriting business with positive recommendations.

positively to upgrades and negatively to downgrades, but only large investors correct for the upward distorted recommendation level. However, we also find the new result that small traders exert buy pressure in response to forecast updates, regardless of whether it is good news or bad news. Large investors, instead, respond to the direction of both forecast and recommendation updates: they exert buy pressure after positive updates and sell pressure after negative updates.⁸

As a result of the distinct responses of small and large investors to recommendations and forecasts, analysts face different costs and benefits to distorting recommendations and forecasts. It is beneficial to bias recommendations in order to induce small-investor trades and please management, and this distortion comes at little cost vis-à-vis large investors, who recognize and undo the upward distortion in their trade reaction. Positively distorted forecasts, instead, do not entail benefits in terms of small-investor reaction. Management pressures reinforce the distinct incentives to distort. While managers like to see optimistic recommendations on their firms they tend to pressure analysts to lower their forecasts shortly before the earnings announcement, allowing the firm to “meet or beat” the earnings forecast (Richardson, Teoh and Wysocki [2004]). Similarly, analysts who have a cautious earnings forecast on a firm may attempt to appease the firm’s management with bullish recommendations. As a result, strategic distortion should be more positive for recommendations and more negative for forecasts. In fact, if the strategic element is strong enough to overcome the analyst’s baseline beliefs about a firm, we may observe a negative *within-analyst* relationship between recommendation and forecast optimism. If, instead, distortion is non-strategic, both recommendations and forecasts should reflect their over-optimism. For example, if analysts believe that the next earnings announcement will be higher than the consensus, they should issue a “buy,” given the strongly positive returns associated with a positive earnings surprise. The most optimistic analysts issue the most optimistic recommendations and the most optimistic forecasts, resulting in a positive within-analyst correlation.

Note, however, that a positive correlation does not rule out strategic distortion. Even if analysts distort strategically, their beliefs about the prospects of the stock may

⁸ These results are consistent with the findings of Mikhail, Walther, and Willis [2007], who find that small trade volume does not vary with the absolute magnitude of an earnings forecast update, while large trade volume is increasing in the absolute magnitude of an earnings forecast update.

dominate the strategic distortion. Thus, we can conclude little from a positive within-analyst correlation between recommendation and forecast optimism. A negative correlation, however, is unambiguous evidence of a strong strategic component. Hence, our empirical analysis consists of a one-sided test of whether the correlation is negative.

In the third step, we turn to our primary contribution of relating individual forecast optimism to individual recommendation optimism as expressed by the same analyst in his most recent recommendation for the same stock. We find an insignificantly positive coefficient for unaffiliated analysts and a significantly negative coefficient for affiliated analysts. That is, those unaffiliated analysts who express the most overoptimism in recommendations are also most optimistic in their forecasts. Affiliated analysts, instead, who express the most overoptimism in recommendations are most pessimistic in their forecasts. In a separate regression, we show directly that affiliated analysts are more likely to make negative errors in their last forecast before the earnings announcement, allowing the firm to meet or beat the forecast. Overall, strategic distortion dominates the behavior of affiliated analysts, but not of unaffiliated analysts.

Finally, in a fourth step, we use the discrepancy between recommendations and forecasts by the same analyst to construct two individual-level measures of strategic distortion. One is based on the raw difference between recommendation optimism and (normalized) forecast optimism, and one on a refined metric that computes the implied recommendation from outstanding annual and long-term growth forecasts. Both measures illustrate how widespread strong strategic distortion is (44-76 percent even among unaffiliated analysts, depending on the measure) but also how heterogeneous both groups of analysts are. We also show, however, that the inclination to distort strategically is very persistent within analyst. Hence, the comparison of recommendation and forecast optimism is useful in assessing the quality of advice from a particular analyst over time.

Overall, our results suggest that most affiliated analysts and a large fraction of unaffiliated analysts strategically speak in “different tongues” to different audiences, small and large traders. These findings are important not only in light of the large role that security analysts play in financial markets in general, but also because individual investors

take an increasing role in managing their own investments and retirement savings.⁹ A growing literature in household finance is concerned with their biases and suboptimal decision-making (Choi, Laibson, and Madrian [*forthcoming*], Choi, Laibson, Madrian, and Metrick [*forthcoming*], Lusardi and Mitchell [2007], Malmendier and Nagel [2009]). Our results imply that precisely this group of investors receives the least reliable investment advice. Mandatory separation of research and investment banking might reduce strategic upward distortions, but the incentive to communicate differently towards distinct groups of investors will remain.

This paper builds upon, and contributes to, a large literature examining analyst earnings forecasts and recommendations.¹⁰ Several papers analyze whether conflicts of interest explain the upward distortion of affiliated analyst recommendations. The results are mixed: O'Brien, McNichols and Lin [2005] find that affiliated analysts are slower to downgrade stocks from "Buy" or "Hold" than unaffiliated analysts, and are faster to upgrade from "Hold," consistent with underwriting conflicts reducing analysts' willingness to incorporate negative news.¹¹ We extend this update-timing idea to earnings forecasts, which have not been previously examined. We find a stark contrast between the two. Kolasinski and Kothari [2008] provide evidence of strategic distortion among analysts affiliated with acquirers and targets around mergers and acquisitions, which they are able to differentiate from non-strategic distortion in this specific context. Cowen, Groysberg and Healy [2006] examine the distortion of forecasts and recommendations based on whether analyst firms generate revenue from underwriting activity, brokerage commissions, a combination, or pure research. Unlike O'Brien, McNichols and Lin [2005] and Kolasinski and Kothari [2008], they conclude that not underwriting activity but trade generation drives upward distortion. Our paper does not aim at distinguishing the different motivations for strategic distortion. Rather, we assess the relative strength of

⁹ The Federal Reserve's triennial Survey of Consumer Finances found that in 1989 fewer than one third of households had stock holdings, while in each of the surveys after 2000, over fifty percent of households had stock holdings. Similarly, in 1989 only 37% of households had one or more retirement accounts (such as an IRA or 401(k) account), while in 2001 the number was 52.6%.

¹⁰ In addition to the examples cited above, important recent examples are Abarbanell and Lehavy [2003], Barber, Lehavy, McNichols and Trueman [2006], and Barber, Lehavy and Trueman [*forthcoming*].

¹¹ O'Brien, McNichols and Lin [2005] builds on McNichols and O'Brien [1997], who argue that conflicts of interest cause analysts to choose to cover firms for which they are genuinely more optimistic, implying that conflicts of interest and genuine overoptimism co-exist. However McNichols and O'Brien [1997] do not examine affiliated analysts. Our paper complements McNichols and O'Brien by jointly examining recommendations and forecasts to separate the effects of conflicts of interest and genuine optimism.

strategic and non-strategic distortion and illustrate their persistence for a given analyst.

Regarding analysts' response to management pressures close to earnings announcements, Richardson, Teoh and Wysocki [2004] document the within-year "walk-down" in earnings forecasts: For annual earnings, analysts issue overly optimistic forecasts near the beginning of the year and overly pessimistic forecasts closer to the annual earnings announcement. Chan, Karceski and Lakonishok [2003] argue that analysts strategically adjust earnings forecasts downwards so that firms avoid negative earnings surprises and find consistent evidence of positive earnings surprises. Baik and Yi [2007], in a concurrent paper, document that firms meet or beat the forecasts of affiliated analysts more often than those of unaffiliated analysts, which is consistent with our own results.

The hypothesis of this paper that security analysts use recommendations and earnings forecasts differently and communicate to different classes of investors "in two tongues" is new to the literature, as is the empirical evidence on the relative importance of strategic and non-strategic distortion using individual-level metrics. As such, many of our specific tests are unique: prior literature does not examine within-analyst correlation of optimism in recommendations and earnings forecasts, and does not examine the effect of underwriting affiliation on earnings forecasts which occur just before an earnings announcement. Other tests are closely related to those performed in prior literature, as discussed above. However, while various papers have examined aspects of analyst optimism in recommendations and in forecasts, few papers have examined both together. It is only in examining both forecasts and recommendations that we can test whether analysts "speak in two tongues." As mentioned above, two notable exceptions are Ertimur, Sunder and Sunder [2007] and Loh and Mian [2006]. Both show that analysts who issue more accurate earnings forecasts also issue more profitable recommendations, at least for firms for which earnings are relevant for the stock price. Their evidence supports our hypothesis that genuinely optimistic analysts will reveal optimism in both forecasts and recommendations. However neither paper examines optimism and pessimism of forecasts and recommendations, as we do in this paper.

The remainder of the paper is organized as follows. In Section 1, we show the aggregate differences in recommendation and forecast optimism between affiliated and unaffiliated analysts. Section 2 examines the trade reactions of small and large investors to recommendations and earnings forecasts. Section 3 presents a within-analyst analysis

of recommendation and forecast optimism. Section 4 constructs within-analyst measures as instruments to detect strategic distortion (“forensic accounting”). Section 5 concludes.

1 Recommendations versus Forecasts: Aggregate Analysis

We start our empirical analysis by evaluating the distortion of recommendation and forecast separately for unaffiliated and affiliated analysts.

1.1 Data

We obtain analyst recommendations, annual (split-adjusted) earnings forecasts, the corresponding earnings-per-share realizations, and information about the analyst identities and brokerage firms from IBES. Recommendations are available starting from October 29, 1993. However during the first three months the IBES data contains an unusually high number of recommendations.¹² We thus choose February 1994 as the start of our sample period, but replicate all results for the full period, in both cases until the end of 2002. We also analyze a shorter period, through July 2001, to exclude the “scandal effects” from 2001 and 2002. For the majority of our analyses the choice of period does not affect the results, and we show results for the longer period. We show both results for Table VI, where the results do vary. Our primary sample of firms with earnings forecast or recommendations during the sample period (February 1994 through December 2002) contains 2,514 securities for 2,484 firms, as measured by 8- and 6-digit cusips respectively.

IBES converts the recommendation formats of different brokerage houses into a uniform numerical format. Like other authors [Jegadeesh et al. 2004], we reverse the coding to the more intuitive scheme: 5=strong buy, 4=buy, 3=hold, 2=sell, 1=strong sell. A “higher” recommendation is better, and an “upgrade” translates into a positive change in the numerical value. We use earnings forecasts occurring between the prior announcement and the announcement to which the forecast relates. We eliminate forecasts relating to announcements that occur outside of the SEC mandated reporting window of 0-90 days after the end of the fiscal year. IBES reports recommendations and earnings forecasts in separate files. In order to match a recommendation with the same analyst’s earnings forecast, we use the analyst identity files of each dataset, which maps

¹² In all other months, the number of recommendations per year and even per month is fairly uniform. the high numbers until the end of January 1994 may have to do with large layoffs in the securities industry during at that time; but they also leave room for concerns about data consistency within the IBES sample.

from numeric analyst identification codes to names.¹³ For most of our analyses, we limit the sample to forecasts with an identified analyst, which eliminates 1.4 percent of forecasts (6,468 out of 460,936 forecasts).

Distortion benchmarks. Our proxy for “optimism” is the difference between an analyst’s forecast or recommendation and the existing consensus. Since earnings forecasts are measured in earnings-per-share (in dollars), we normalize the difference by share price on the date of the earnings forecast.¹⁴ For annual earnings forecasts, the consensus is the average of all outstanding forecasts made after the prior annual earnings announcement.¹⁵ For recommendations, the calculation is similar. Since recommendations do not apply to a specific time period, we use a range of periods: one, two, six, and twelve months of prior recommendations. (We show the one-month results.) Both consensus calculations closely resemble those made in practice, e.g. by IBES (for forecasts) or *Yahoo! Finance*.

Affiliation. Our affiliation measures are based on the underwriting relationship of the analyst’s brokerage house with the firm the analyst is reporting on. As in previous literature,¹⁶ analysts are affiliated if their investment bank was the lead or co-underwriter of an initial public offering (IPO) in the past five years or of a seasoned equity offering (SEO) in the past two years. We use the SDC New Issues database to obtain underwriting data from 1987 to 2002. We link IBES broker firms and SDC underwriters with the company names provided by the IBES recommendation broker identification file and the SDC database. We improve the match using company websites and news articles, in particular to determine subsidiary relationships and corporate name changes. Finally, we use the mapping from Kolasinski and Kothari [2008] to identify additional matches.¹⁷

1.2 Differences in Means

We first examine the summary statistics of recommendations and earnings forecasts in

¹³ Since IBES acknowledges deviations between the “amaskcd” variable in the recommendations file and the “analyst” variable in the forecasts file, we complement the numeric match with a combination of programmed name-matching and hand-matching.

¹⁴ As a robustness check, we replicate our optimism analyses dividing the difference between earnings forecast and consensus by the absolute value of the consensus, creating a percentage measure.

¹⁵ For example, if an annual earnings announcement is expected to be made in February 2000, we start from the set of all forecasts made after the February 1999 earnings announcement. For any given firm on any given day, we then use the most recent forecast of each analyst and calculate the average.

¹⁶ Lin and McNichols [1998]; Michaely and Womack [1999].

¹⁷ We are grateful to Adam Kolasinski and S.P. Kothari for providing us with their mapping, which uses corporate websites, LexisNexis, Hoover’s Online, and the Directory of Corporate Affiliations.

the IBES-SDC merged dataset. In the left half of Panel A, Table I, we display the distribution of recommendations both for the full set of analysts and separately for unaffiliated and affiliated analysts. As in previous literature, we find that the vast majority of recommendations are positive or neutral; fewer than 5% are “sell” or “strong sell.” The proportion of “buy” and “strong buy” recommendations is even higher for affiliated analysts, resulting in a significantly higher mean recommendation for affiliated than for unaffiliated analysts. Analysts whose brokerage houses do not underwrite *any* security issuance during the 1987-2002 period, denoted as “Never Affiliated,” have the least positive recommendations and the most sell and strong sell recommendations.

The observed differences in recommendation level are likely to be affected by differences between firms covered by affiliated and unaffiliated analysts. For example, firms that access the capital market for external financing may have better prospects. In the lower half of Panel A, we eliminate this sample heterogeneity by restricting the sample to firms that can have affiliated analysts, i. e., firms that had an SEO during the past 2 years or an IPO during the past 5 years. In this subsample, unaffiliated recommendations are more positive, with a mean of 3.87 compared to 3.77 in the full sample. However, affiliated recommendations are still significantly higher, with a mean of 4.02.

Turning from recommendations to annual earnings forecasts, we find that the pattern reverses. As shown in the right half of Panel A, the average forecast is \$1.68 per share. Forecasts tend to be positive, with even the 25th percentile being \$0.78. In sharp contrast to recommendations, affiliated analysts issue significantly *lower* forecasts than unaffiliated analysts, with an average of \$1.37 compared to \$1.68. As shown in the lower part of Panel A, this pattern also holds in the sample of recent security issuers: affiliated forecasts are significantly lower than unaffiliated forecasts, though the difference is much smaller (7 instead of 31 cents), confirming significant sample heterogeneity.¹⁸

This discrepancy persists when evaluating recommendations and forecasts relative to their consensus. At the time of issuance, affiliated recommendations are significantly more often above the consensus (56%) than unaffiliated recommendations (49%), while affiliated and unaffiliated forecasts are very similar relative to the consensus (47% and

¹⁸ While our recommendation results confirm the findings in Lin and McNichols [1998], the reversed pattern for forecasts differs from their finding (no differences). In addition to the different sample period (1989-1994), sample selection is a likely explanation. Lin and McNichols [1998] only consider forecasts issued just before and just after a seasoned equity offering.

45% above the consensus at the time of issuance.) The pattern becomes slightly stronger when focusing on the subsample of firms with recent security issuances: The difference in recommendations becomes larger, with 48% unaffiliated recommendations above the consensus, and the difference in forecasts entirely disappears, with 47% of unaffiliated forecasts above the consensus.

Table II repeats the comparison relative to the respective consensus in a regression framework. Given the observed heterogeneity between firms with and without recent equity issuance, we restrict the analysis to recent issuers, as in the lower half of Panel A in Table I. In Column 1, we regress the difference between recommendation levels and consensus on an indicator for affiliation, controlling for year-, month-, and day-of-the-week fixed effects. We find that affiliated recommendation optimism is significantly larger than unaffiliated recommendation optimism. Column 2 shows the same analysis for annual forecasts. Given the strong time patterns in earnings forecast optimism found in prior literature (see also later Table VI), we control for the timing within the fiscal year, in addition to the time fixed effects.¹⁹ We find that affiliated forecast optimism is, instead, significantly *lower* than unaffiliated forecast optimism.

The differences in mean recommendations and mean forecasts between affiliated and unaffiliated analysts is a first indication of a stronger strategic component in affiliated analysts' issuance behavior, relative to unaffiliated analysts. Only strategic distortion can easily explain why persistently more optimistic beliefs about a stock's performance over the next months translate into persistently more negative beliefs about the next annual earnings.

1.3 Differences in Timing

To further separate strategic and non-strategic motivations, we consider the timing of recommendations and earnings forecasts. O'Brien, McNichols and Lin (2005) find that affiliated analysts are significantly faster to upgrade Hold recommendations and significantly slower to downgrade Buy or Hold recommendations than unaffiliated analysts, from their first recommendation following an issuance. We first examine whether this biased updating behavior extends to the longer affiliation period, and then test whether it applies to earnings forecasts. As with the higher mean distortion of recommendations, the

¹⁹ The recommendation results are unaffected if we include the forecast controls for time until announcement in the recommendation regression as well (coefficient 0.0668, s.e. 0.0084).

timing of recommendation updates could be non-strategic: analysts could be genuinely responding more quickly to positive news due to their positive priors and credulity.²⁰ If that is the case, however, forecast updating should exhibit a similar pattern.

Table III, Panel A, shows that affiliated analysts are faster to update negative and hold recommendations than unaffiliated analysts, but preserve their positive recommendations about 70 days longer than unaffiliated analysts. A similar picture emerges if we divide recommendations into upgrades and downgrades, as shown in the last two columns of Panel A. Affiliated analysts wait 68 days longer than unaffiliated analysts before downgrading a stock, while they wait only 8 more days before upgrading. The regression analysis in Panel B, Column 1, shows that affiliated analysts wait 81 days longer than unaffiliated analysts before downgrading a strong buy, 51 days longer until changing a buy, ($t = 5.29$ and 4.07 respectively), but 20 days *less* before changing a hold, sell, or strong sell. (The last number is insignificant, with a t -statistic of 1.3.) As shown in Column 2, we also find that the “strong buys” and “buys” of affiliated analysts are significantly less above the consensus than those of unaffiliated analysts. In other words, affiliated analysts wait until the consensus is high before issuing a positive recommendation and issue negative or neutral recommendations only after a large fraction of recommendations outstanding is on the same lower level. All findings, viewed together, imply that affiliated analysts aim not to “stand out.” Their issuance is timed to coincide with a consensual view of most other analysts covering the stock.

For earnings forecasts we find a very different pattern. Whether we focus on overall forecast frequency or on forecasts above, equal to, or below the consensus, affiliated analysts update at almost exactly the same speed as unaffiliated analysts. As shown in the lower half of Panel A, the differences are often less than a day, and even the largest difference – days until above-consensus updates – amounts only to 2.7 days. The regression analysis in Column 3 of Panel B reveals that only the latter difference is statistically significant. This similarity in forecast updating is, of course, partly shaped by the quarterly schedule of earnings releases. However, affiliated analysts could exploit more of the 90-day interval between quarterly announcements but choose not to do so.

Overall, both the differences in mean recommendations and forecasts and the dif-

²⁰ See Daniel, Hirshleifer and Subrahmanyam [1998] for a discussion of the relevant literature and an application to investor behavior.

ference in the timing of recommendation and forecast updates indicate a strong strategic component in affiliated analysts' issuance behavior, relative to unaffiliated analysts.

2 Investor Response

A necessary condition for analysts to speak in two tongues is that small traders follow recommendations more literally than large traders, but that large traders react more strongly to the information in forecasts. In this section we test whether this is the case.

2.1 Data

The trading data is from the New York Stock Exchange Trades and Quotations (TAQ) database. The TAQ database reports every round-lot trade and every quote from January 1, 1993 onwards on the New York Stock Exchange, American Stock Exchange and NASDAQ. We examine trading of ordinary common shares for US firms traded on the NYSE, matching to our recommendation and forecast data.

Investor type. We separate small and large investors by trading size. Following Lee and Radhakrishna [2000], we choose dollar- rather than share-based cutoffs since they minimize noise in separating individuals from institutions, and allow for a buffer zone (\$20,000-\$50,000) between small and large trades.²¹ Malmendier and Shanthikumar [2007] show that these proxies are effective measures of individual and institutional trades until about 2000. As they discuss, the small portfolio size of most individual investors ensured that their trades remained below \$50,000, and the distribution of trade sizes on the NYSE remained quite stable from 1993 through 2000. However, the distinction between “small” and “large” trades begins to disappear in the early 2000's. Thus, we limit our study to trades from 1993 through 2002, as in Malmendier and Shanthikumar [2007].

Trade Reaction. We employ measures of “directional trade reaction” (trade initiation) to capture the buy and sell pressure exerted by traders. We use the modified version of the Lee and Ready [1991] algorithm, developed in Odders-White [2000], to determine who initiated the trade, the investor buying or selling. The algorithm matches a trade to the

²¹ The cutoffs are derived from the three-month TORQ sample from 1990-91, in which actual information on the identity of traders was available to check the accuracy of the trade-size based classification method. The results are robust to several variations (\leq \$5,000; \$5,000-\$10,000; \$10,000-\$20,000).

most recent quote that precedes the trade by at least 5 seconds. If a price is nearer the bid (ask) price it is classified as seller (buyer) initiated. If a trade is at the midpoint of the bid-ask spread, it is classified based on a “tick test.” The tick test categorizes a trade as buyer-initiated (seller-initiated) if the trade occurs at an uptick (downtick), i.e., if the price is higher than the price of the previous trade. We drop trades at the bid-ask midpoint, which are also the same price as in preceding trades.²² The raw trade imbalance for firm i , investor type x , and date t is calculated as

$$(1) \quad TI_{i,x,t} = \frac{buys_{i,x,t} - sells_{i,x,t}}{buys_{i,x,t} + sells_{i,x,t}}$$

We normalize by subtracting off the firm-year mean, and dividing by the firm-year standard deviation, separately for each investor type, as in Shanthikumar [2003]²³:

$$(2) \quad TI_{i,x,t}^{abnormal} = \frac{TI_{i,x,t} - \overline{TI}_{i,x,year(t)}}{SD(TI_{i,x,year(t)})}$$

The adjustments are made by year to account for changes in trading behavior over time and by firm to adjust for any consistent differences in trading across firms. These normalizations allow us to compare abnormal trading behavior over time, among firms, and across small and large investors, and replace year- and firm-fixed effects in the regression framework.

Panel B of Table I displays the sample statistics of small and large trade reactions. As before, we restrict the analysis to recent equity issuers. The first three columns (“All dates”) display statistics for the full sample, the next three columns (“Recommendation dates”) for recommendation days and the last three columns (“Earnings forecast dates”) for earnings-forecast days. Small traders initiate more trades than large traders, over twice as many in the full sample. The gap is smallest on earnings-forecast dates when small traders still make 48% more trades than large traders. Both groups increase their buy and their sell pressure on recommendations and earnings-forecast days. All results are similar if expressed in dollar values rather than number of trades.

²² The original Lee-Ready algorithm employs a “zero-tick” in the case that a trade is at the bid-ask midpoint and the same price as the previous trade. Because of its low accuracy (about 60% according to Odders-White, 2000) the “zero-tick” is left out in the modified Lee-Ready algorithm.

²³ See also the measures in Lee [1992] and Hvidkjaer [2001].

2.2 Analysis

Table IV displays trade reactions to updates of recommendations (Columns 1-3) and earnings forecasts (Columns 4-6), separately for unaffiliated and affiliated updates. Trade reaction is measured as the sum of abnormal trade imbalances, as defined in Equation (2) above, over trading days 0 and 1 relative to the forecast and recommendation dates.

For recommendation updates, the reactions of both small and large traders are significantly positive: all traders exert more buy pressure when the recommendation of an analyst for a given stock increases. However, the coefficient of small traders—but not that of large traders—is even higher for affiliated recommendations. Moreover, small traders also have higher intercepts for both groups than large traders, i.e., they exert more buy pressure across all levels of recommendation. The results confirm the findings in Iskoz [2002], Malmendier and Shanthikumar [2007], and Mikhail, Walther, and Willis [2007] that large investors discount recommendations while small investors follow them literally. For example, Malmendier and Shanthikumar [2007] show that while small investors display no significant reaction to a hold recommendation and a buy reaction after buys, large investors react *negatively* to hold and display no reaction after buys. In addition, large traders shift their reaction to recommendations even more downwards when an analyst is affiliated.

For annual forecast updates, a very different picture emerges. Large traders' reaction to an increase in an analyst's forecast for a given stock (normalized by share price) is significantly positive, both for unaffiliated and for affiliated analysts. In contrast, small traders react significantly positively on the day of a forecast update (intercept) but not in the direction of the update. Instead, the slope coefficient is insignificantly negative. Both sets of results are very similar if we restrict the analysis to recommendations and forecasts by those analysts who are simultaneously affiliated and unaffiliated in at least one stock at the time they issue their recommendation or forecast.

In summary, large investors react much more strongly to the direction of earnings forecasts than small investors, while small traders react positively regardless of whether the forecast update is positive or negative. Small investors' trade reaction to recommendations, instead, is stronger, both directionally and in absolute terms. As a result, upward distortion of recommendations has lower costs and larger benefits than upward distortion of forecasts and should thus be stronger if the analyst is distorting strategically. More-

over, as discussed above, management pressures to lower earnings forecasts close to the announcement imply that strategic forecast distortion might, in fact, be negative. While small investors generally do not process the good or bad news contained in forecast updates, they seem to respond to the simple headline of firms “meeting or beating” the consensus forecast.²⁴ As a result, differential upward distortion of recommendations and downward distortion of forecasts implies a strong strategic motivation.

3 Recommendations versus Forecasts: Individual-level Analysis

The discrepancies in affiliated and unaffiliated recommendations and forecasts – both in means and in timing – indicate that affiliated analysts are strategically distorting relative to unaffiliated analysts. In this section, we establish the dominant motivation for upward distortion – strategic versus non-strategic optimism – *within* the groups of affiliated and unaffiliated analysts (rather than relative to each other). Linking individual-level measures of recommendation distortion and of forecast distortion, this analysis also allows us to address the concern that the higher strategic distortion of affiliated analysts reflects subsample heterogeneity, e.g., different sets of analysts, different subsamples of stocks, or different times at which investment advice is issued. (We have ruled out heterogeneity between firms who did or did not access equity markets.) The individual-level analysis, instead, holds constant the identity of the analyst, the stock, and the time. In Section 4, we will use the within-analyst measures to construct distortion metrics and to measure the heterogeneity in strategic behavior.

Within-Analyst Correlation between Recommendations and Forecasts. We first test whether a given analyst who has a particularly positive recommendation outstanding also issues more positive earnings forecasts for the same stock. We directly link recommendations and forecasts by analyst and compare their relative “optimism,” measured as the difference to the respective consensus. We aim at including only forecasts issued after the last quarterly announcement prior to the annual announcement to ensure that all forecasts

²⁴ Kasznik and McNichols (2002) find that the market reaction to meeting or beating the consensus forecast is significantly stronger for firms with below-median analyst coverage and, hence, for firms with little institutional ownership (p. 755). See also Bhattacharya et al. (2007), who find that small traders respond strongly to IBES-based earnings surprises, while large traders do not. (Also note that the result of a stronger reaction for institutional investors reported in Battalio and Mendenhall (2005) refers to Compustat earnings minus forecast rather than the consensus-based earnings surprise.)

reflect the last quarterly numbers. The timing of last (pre-annual) quarterly earnings announcement, however, varies. It typically happens 90-100 days before the annual earnings announcement, but there is also a large number of quarterly announcements between 83 and 90 days before the annual announcement.²⁵ Only after 83, the number of cases drops sharply. To insure both that all forecasts incorporate the last quarterly announcement and to have a common time frame until the annual announcement, we consider all forecasts issued within 80 to 1 days prior to the annual earnings announcements. (As a robustness check, we redid the analysis for each time period from $[-81,-1]$ to $[-89,-1]$. All results are very similar. The effects are strongest for 82 days, consistent with the drop in quarterly announcements after 83 days.) As before, we also limit the sample to recent issuers.

Table V reports the results. Panel A displays the relationship between annual earnings forecasts and recommendations outstanding at the time of the forecast, i.e., recommendations issued on the same day as the forecast or on a prior day.²⁶ As in Table II, we include year-, month-, and day-of-the-week fixed effects. (The results are virtually identical without the fixed effects.) For the whole sample and for the subsample of unaffiliated analysts, we find insignificantly positive coefficients. For affiliated analysts, instead, the coefficient of recommendation optimism is significantly negative, with a one-tailed t-test rejecting that the relationship is positive at $p = 0.03$. Hence, the more positive an affiliated analyst's recommendation is relative to the existing consensus, the more negative is the same analyst's same-stock earnings forecast relative to the consensus. If we leave out the fixed effects, we can also observe that the unaffiliated and the affiliated intercepts are, instead, very similar. The discrepancy in affiliated forecasts and recommendations indicates that affiliated analysts are, on average, significantly affected by strategic motives. In untabulated regressions, we repeat the analysis conditioning on the recommendation level. As expected under strategic distortion, the negative relationship between affiliated forecast and recommendation optimism is strongest for buy and strong buy recommendations.

The pooled regression in the last column shows that affiliated analysts issue

²⁵ The modal point in the IBES universe is 98 days (5,635 prior-to-annual quarterly announcements). The second-highest frequency is for 91 days (4,491 observations). There are between 168 and 876 observations for each of the 83- to 90-day periods, and the number of observations drops below 100 for 82 days and less.

²⁶ About a quarter of forecasts are accompanied by a new recommendation on the same day.

lower earnings forecasts than unaffiliated analysts for a given level of outstanding recommendation ($t = 1.90$, two-tailed p -value = 0.058). The difference is large: For a one standard deviation increase in recommendation optimism, unaffiliated analysts increase their average forecast slightly, reducing their pessimism relative to the consensus by 5.3% (evaluated at the average forecast “optimism” [multiplied by 100] of $-.2193$). Affiliated analysts, instead, decrease their forecast further, increasing their pessimism by additional 58.1%. This finding confirms the results we obtained from comparing the mean affiliated and unaffiliated distortion, now controlling for subsample heterogeneity. That is, we can now rule out that the result is due to different analysts issuing recommendations and forecasts, to different stocks driving the recommendation and forecast results, or to the differences in timing.

In Panel B, we reduce the heterogeneity even further and consider only analysts who are both unaffiliated and affiliated in at least one stock at the time they are issuing their forecast. Thus, by analyzing unaffiliated and affiliated distortion separately, we test whether changing incentives make the same analyst more or less strategic. The full-sample coefficient becomes negative but remains insignificant. The coefficient estimate on unaffiliated recommendation optimism becomes three times larger, though it remains insignificantly positive. The coefficient on affiliated recommendation optimism is virtually identical to that in Panel A. As a result, the discrepancy between affiliated and unaffiliated behavior becomes even stronger. In terms of economic significance, a one standard deviation increase in recommendation optimism induces unaffiliated analysts to reduce their pessimism relative to the consensus by 15.5% (evaluated at the average forecast “optimism” [multiplied by 100] of $-.2196$), while affiliated analysts decrease their forecast further, increasing their pessimism by additional 59.4%. The results show that the incentives arising from affiliation are strong enough to cause significant changes in the behavior of a given analysts.

Accuracy. We also find that, despite their informational advantages, affiliated analysts are not more accurate than unaffiliated analysts, confirming earlier findings in Dugar and Nathan [1995]. We measure accuracy either as (1) absolute forecast error, forecast minus realization, normalized by share price or as (2) relative forecast error rank, as defined by

Mikhail, Walther and Willis [1999].²⁷ We use the full sample of forecasts (of recent equity issuers) and control for the time remaining until the earnings announcement. In untabulated regressions, we find that affiliated analysts exhibit significantly lower accuracy using measure (1) ($t = 1.94$) but insignificantly lower accuracy using measure (2). Limiting the sample to analysts who are currently both affiliated and unaffiliated, we find no significant differences in the forecast accuracy for stocks with and without affiliation using measure (1) and significantly lower accuracy using measure (2) ($t = 2.90$).

Moreover, we can show that affiliated analysts' sacrifice accuracy particularly for their last forecasts before the announcement. While unaffiliated analysts significantly improve their accuracy in the last nine days, compared with days 10-80, affiliated analysts do not. The additional analysis in the next subsection (Table VI) reveals a large degree of distortion in the last forecast of affiliated analysts prior to the announcement, which, as we argue, allows the firms to "meet or beat" the earnings forecast.

Forecasts Immediately Prior to Announcements. The negative within-analyst correlation in forecast and recommendation optimism confirms that affiliated analysts "speak in two tongues." As discussed above, strong strategic distortion predicts a negative correlation, rather than no or a "less positive" correlation, due to management pressures to lower earnings forecasts close to the announcement.

To further test this explanation, we examine whether an analyst's last earnings forecast before the announcement is above the announced earnings (positive forecast error) or below (negative forecast error). If affiliated analysts issue lower forecasts strategically to allow management achieve positive earnings surprises, their likelihood of negative forecast errors should be higher. We estimate a logit model, regressing a dummy for positive forecast error on indicators for affiliation type and controls for the expected time to the next annual earnings announcement. Table VI presents the results. In the first two columns, we use the usual sample period. In the last two columns, we repeat the analysis for the pre-scandal period until August 1, 2001. The cutoff reflects that media coverage of analysts' conflicts of interest skyrocketed in August 2001, after Morgan

²⁷ The "relative forecast error rank" measure ranks all analysts covering a stock for a given period by the forecast error of their last forecast during the period, normalized by the total number of analysts covering the firm. The resulting rank ranges from 0 to 1. Measure (1) uses all forecasts, while measure (2) uses only analysts' last forecast before the announcement.

Stanley settled a suit against the high-profile analyst Henry Blodget and additional suits were filed against Morgan Stanley's "star technology analyst" Mary Meeker (Financial Times, 2001). The shorter period contains 2,362 securities for 2,337 firms.

We find that affiliated analysts are more likely to issue final forecasts below the realization, insignificantly so in the full sample period and significantly (at the 10 percent level) in the pre-scandal period. The results are statistically significant also in the full sample period for IPO lead-underwriters. The results are similar even after adding a control for the optimism expressed in the earnings forecast (Columns 2 and 4), though the statistical significance is further diminished. That is, even for the same deviation from the consensus, a forecast is particularly likely to be too low if issued by an affiliated analyst. Overall the more pessimistic forecasts of affiliated analysts appear to be strategically designed to "please management."

Timing. The timing results in Section 1.3 suggested that affiliated analysts "hide in the crowd" when issuing a positive recommendation, not deviating too much from the consensus, and then delay downgrading. As a result, affiliated recommendations that have been outstanding for a while tend to be significantly more positive than the current consensus. Consistent with this interpretation, Table V implies that affiliated analysts should downgrade their outstanding recommendation at the time they are issuing their forecast, to be consistent with the more pessimistic forecast, but decide not to do so. A second implication then is that, at the point affiliated analysts finally update their recommendation, the correlation between the optimism of the new (on average lower) recommendation and the *previously* issued, more pessimistic forecast should be less negative or even positive.

This second implication holds in the data. In untabulated regressions, we repeat the analysis of Table V using the analyst's *next* recommendation after the forecast (rather than the same-day or past recommendation) and calculate forecast optimism and next-recommendation optimism, both relative to the respective consensus as of the day of the forecast.²⁸ Since the next recommendation may occur after the firm's earnings announcement (in which case it is affected by the actual announcement), we include interactions with "before announcement" and "after announcement" dummies. The relevant (before-announcement) interaction for affiliated analysts turns from significantly negative to

²⁸ Alternatively, we evaluated the optimism in the next recommendation at the time of the next recommendation. The results are very similar, both in economic and statistical magnitude.

significantly positive, while the coefficient for unaffiliated analysts remains insignificant. In other words, affiliated forecasts are on average more consistent with future than with simultaneous recommendations. With some delay, affiliated analysts incorporate the negative information into their recommendations, and the relation between the optimism in their forecast and in their *next* recommendation becomes insignificantly positive.

4 Forensic Accounting—Measuring Analyst Distortion

The within-analyst correlation in recommendation and forecast optimism shows that, on average, affiliated analysts “speak in two tongues:” their strategic motivation strongly affects the investment advice they issue. For unaffiliated analysts, instead, strategic distortion does not dominate other determinants enough to be detected in the data, at least on average. Going beyond averages, we now use the discrepancy between recommendation and forecasting behavior to construct individual-level measure of strategic distortion. The measures are specific to a given analyst, covering a particular firm at one point in time, and are meaningful for both affiliated and unaffiliated analysts. These measures will allow more insights into the distribution and heterogeneity of strategic distortion among analyst, and they allow testing for within-analyst persistence in strategic distortion across stocks. In fact, if we do find persistence, the comparison of recommendation and forecast optimism provides a useful tool in assessing analysts over time.

We develop two measures of strategic distortion, one raw metric based on the difference between recommendation and (normalized) forecast optimism and one refined metric based on the difference between recommendations and “forecast-implied” recommendations. While the first approach provides an untainted view of the raw data, the second approach is more sophisticated in relating recommendations to forecasts but also requires specific assumptions.

The construction of the first measure is illustrated in the left column of Figure 1. The top figure displays the distribution of recommendation optimism, defined as recommendation minus consensus recommendation as of the day of the recommendation in question. (As always, recommendations are coded numerically ranging from 1 for strong sell to 5 for strong buy.) The vast majority of observations lie in the interval from -2 to +2. The middle figure displays earnings forecast optimism, defined as earnings-per-

share forecast minus consensus, normalized by share price. In order to make the economic magnitudes compatible with recommendations, forecast optimism is then multiplied by 100 and winsorized at the 1% tails. Again, the vast majority of observations lie in the interval from -2 to +2. Our first metric is defined as the difference between these two, recommendation optimism minus scaled forecast optimism, shown in the bottom figure. The scale is comparable to that of recommendation optimism, which naturally ranges from -4 to +4. We see that the majority of observations lie again in the interval from -2 to +2, but also that the distribution is skewed to the right.

The statistics in the upper half of Panel A in Table VII confirm the right skewness: the mean of this first measure is 0.25 but the median is 0.06 and the 25th and 75th percentile are -0.42 versus +0.92. Overall, 76% of recommendation-forecast comparisons result in strictly positive values, indicative of dominant strategic distortion. Consistent with our prior results, a larger fraction of affiliated analysts (82%) distort strategically, resulting in a significantly higher mean distortion than among unaffiliated analysts, but also the fraction of unaffiliated analysts with a dominant strategic component is high (76%). At the same time, a significant fraction of both affiliated and unaffiliated analysts (17% and 24%) do not distort enough to be classified as strategic with our measure. All results are virtually identical if we restrict the analysis to analysts who are simultaneously affiliated and unaffiliated, as shown in the upper half of Panel B.

The heterogeneity in strategic distortion appears even larger when we refine the “raw” comparison of recommendations and forecasts. For our second measure, we take the difference between the actual recommendation and the “forecast-implied” recommendation, i.e., the recommendation implied by the analyst’s earnings-per-share and long-term-growth forecasts according to the price-earnings-growth (PEG) valuation model. Bradshaw (2004) reports that analysts use the PEG model to translate their earnings and long-term-growth forecasts into recommendations and shows that the PEG model exhibits indeed a significant relationship with recommendations. Hence, the PEG model can be used to relate analysts’ earnings forecast to their recommendations.²⁹ The PEG model uses analysts’ long-term-growth forecasts (in percent) as a multiplier for their

²⁹ Bradshaw (2004) also estimates the relationship between analyst recommendations and several other valuation models: two residual income models and analysts’ long-term-earnings growth. He finds that neither residual income model explains recommendations, while long-term-growth forecasts, like the PEG model, exhibits a significant relationship with recommendations.

earnings-per-share estimates. The relationship between the resulting target price T and the current share price P determines the implied recommendation³⁰: it is strong buy if $T/P > 1.5$, buy if $T/P > 1$, hold if $T/P > 0.75$, sell if $T/P > 0.5$, and strong sell if $T/P \leq 0.5$. Because the model is based on an earnings-multiplier approach, we need to restrict the sample to positive earnings and long-term-growth forecasts to avoid a negative target price. The sample size still increases relative to measure 1 since we can include recommendations for which we do not have recommendations in the prior month and hence no consensus measure. (All statistics are very similar for both measures in the subsample of observations for which both measures are defined.³¹)

The construction of this measure is illustrated in the right column of Figure 1. The top figure simply displays the distribution of recommendations. We see again the well-known fact that the vast majority of recommendations are neutral or positive, with only 2.3% negative recommendations. The middle figure displays “forecast-implied” recommendation levels. The distribution is also strongly skewed to the right, with 61% forecast-implied strong buy recommendations. The frequencies of the other four categories, however, are much more uniform, ranging from 8% to 12%. The bottom figure displays the difference between recommendations and forecast-implied recommendations, ranging all the way from -4 to +4. The graph shows that, according to this measure, positive and negative distortions are more balanced than under the first, “raw” measure. In fact, as shown in the lower half of Panel A in Table VII, the mean is only slightly positive (0.08), though again significantly larger for affiliated than for unaffiliated analysts (0.16 versus 0.07). Median, 25th percentile and 75th percentile are identical for the whole sample and the subgroups of affiliated and unaffiliated analysts (0, -1, +1), due to the discrete nature of the measure. We see that the percentage of negative distortions according to this measure (29%) is not very different from the first measure (23%), but a large number of observations display zero distortion, resulting in only 52% positively distorted observations. The results are, again, very similar for the subset of analysts who are both affiliated and unaffiliated, shown in the lower half of Panel B. It is noteworthy that the

³⁰ We calculate the target price as $T = (EPS * (1 + LTG/100)) * LTG$. Bradshaw (2004) uses two-year-ahead earnings forecasts. To match the scaling in Bradshaw (2004) but maintain consistency with the rest of our paper, we use the one-year-ahead earnings forecast, but scale it assuming that the analyst believes earnings will grow at the analysts’ long-term-growth forecast rate.

³¹ For example, in the overlapping subsample (49,516 observations), the mean of measure 1 for all, unaffiliated, and affiliated analysts are 0.22, 0.21, and 0.40 and the means of measure 2 are 0.10, 0.10, and 0.17.

mean distortion for unaffiliated analysts is negative. Also, while the percentage of negative values is always higher for unaffiliated than for affiliated analysts (29% versus 26% in the full sample and 32% versus 26% in the sample of analysts who are both affiliated and unaffiliated), the percentage of positively distorted observations is slightly higher in the full sample (52% versus 51% in Panel A) but reverts to the usual order once we control for heterogeneity of analysts by restricting to those who are both affiliated and unaffiliated (44% versus 51% in Panel B).

In summary, both measures illustrate that strategic distortion is widespread, even among unaffiliated analysts, but, at the same time, that between a quarter and half of the observations do not display (enough) signs of acting strategically to be captured by our measures. Note that both measures become more similar if we restrict the sample statistics to “high-quality analysts” as measured by making the annual “All-Star Analyst” list of Institutional Investor Magazine. For all-star analysts, the mean distortion is 0.28 under the first measure and 0.25 under the second measure. Under the first measure, all-star analysts display no significant difference in distortion measure when affiliated vs. unaffiliated (0.31 versus 0.27, p -value = 0.15), while the difference remains significant under the second measure.

As a final step, we illustrate that the two distortion metrics have significant predictive power for individual analyst behavior over time. That is, while our analysis so far illustrated that a given analyst distorts more if affiliated than if unaffiliated, we now show that there are also significant analyst fixed effects.

A simple way to evaluate the persistence of strategic distortion in a given analyst is to ask how the likelihood of future strategic distortion depends on whether the analyst distorted strategically in the past. We calculate these transition probabilities for the two distortion metrics using zero as a cutoff point, i.e., considering each observation with a value strictly larger than zero as an instance of strategic distortion. Table VIII displays the transition matrices for both measures. For the whole sample of analysts, shown in the upper left corners of both panels, we find that a strategic distorter will again distort strategically for the same stock with 84%-89% probability, while an analyst who did not distort strategically will start doing so for the same stock with only 50% or even 9% probability, depending on the measure. Thus, under both measures, analysts are much more

likely to distort strategically if they did so before. One reason why the discrepancy is even larger under measure 2 than under measure 1 is that the PEG formula uses long-term growth forecasts, which are typically outstanding for a longer period. All statistics are extremely similar if we restrict the sample to analysts who are simultaneously affiliated and unaffiliated: 83%-88% probability for strategic distorters versus 53%-8% for analysts who did not distort strategically.

Part of this persistence in strategic distortion reflects, however, that affiliation for the same stock persists as well. Hence, we next consider persistence over *all* stocks covered by an analyst (second row). Here, an analyst who distorted strategically is likely to do the same in the next observation with 79%-72% probability, while an analyst who did not distort strategically, will start distorting strategically only with 69%-30%. Hence, while the discrepancy is diminished it remains large and significant. All percentages are very similar after excluding the same stock, as shown in the third row of both panels: 79%-70% for strategic distorters and 67%-32% for other analysts.

We can go further in disentangling personal fixed effects from affiliation effects: we distinguish whether an analyst is affiliated or unaffiliated in the original observation and in the next observation. All transition probabilities are shown in the lower right blocks of both panels in Table VIII. For measure 1, we see that if an affiliated analyst distorted strategically in the past, his next observation is very likely to display strategic distortion if the analyst is again affiliated (86%) but also quite likely if unaffiliated (78%). The percentages are very similar for strategic distorters who were unaffiliated: 82% if the analyst becomes affiliated and 79% if the analyst remains unaffiliated. Those who are not strategic distorters with the current forecast are consistently less likely to issue a subsequent distorted forecast, regardless of whether they are affiliated or unaffiliated now, and whether their next forecast is affiliated or unaffiliated. In other words, our results show strong persistence in strategic distortion over time, in addition to the effects of affiliation.

The percentages are very similar if we calculate the above statistics for affiliated analysts and their next affiliated and next unaffiliated observation (whether it is the immediately following one or a later one), and, similarly, for unaffiliated analysts and their next affiliated and next unaffiliated observation. As shown in the last two rows of each panel, all statistics are virtually identical, at most deviating by one percentage point.

Under measure 2, the percentages are generally lower but the discrepancies between past strategic distorters and non-(strategic) distorters are larger. As with the first measure, we observe large persistence in strategic distortion, whether or not the analyst was affiliated in the past and whether or not he is affiliated in the next observation.

Overall the results in this section indicate significant fixed effects in analyst behavior, above and beyond the distortive incentive effects due to affiliation. As a result, examining the discrepancy in analysts' views across different types of information provision can be used to identify those analysts who are most affected by incentive distortions and to assess the quality of future investment advice by a given analyst.

5 Conclusion

This paper provides a novel empirical approach to disentangle strategic and non-strategic motivations to distort recommendations upwards. We show that, compared to unaffiliated analysts, affiliated analysts issue more positive recommendations but more negative forecasts. In addition, recommendations and forecasts are negatively correlated within analyst for affiliated analysts, but positively for unaffiliated analysts. Additional results on the timing and updating of recommendations and forecasts suggest that affiliated analysts “hide in the crowd” when issuing new recommendations, but then maintain positive recommendations longer than unaffiliated analysts.

Our findings suggest that affiliated analysts strategically choose to display optimism about the firms they cover in one outlet, recommendations, which are consumed most directly by small investors. They abstain from doing so in another outlet, earnings forecasts, which are consumed most directly by large investors. Instead, they distort the last forecast before the announcement downwards, consistent with management pressures to provide “beatable” forecasts. The stronger inclination of affiliated analysts to distort strategically holds even within analyst, i.e., comparing the same analyst's behavior for stocks with which he is affiliated and for stocks with which he is unaffiliated.

In addition to the affiliation effects, we also identify significant analyst fixed effects. We develop two measures capturing the discrepancy in recommendation and forecasting behavior and show that an analyst who displayed strategic distortion once is

extremely likely to do so again while an analyst who did not distort strategically when covering a stock is much less likely to do so at the next instance.

Our findings have implications for policy debates about the appropriate regulations to be imposed on brokerage houses. Given the strong results for affiliated analysts, our results corroborate the importance of eliminating misaligned incentives due to affiliation. The persistence results, however, imply that some analysts are generally more inclined to distort strategically, above and beyond affiliation incentives. While our results do not imply a solution to the distortion problem, our measures of strategic distortion can provide a useful tool to identify a candidate group of strategic distorters. The same applies to a broader realm, beyond analyst behavior. The phenomenon of “speaking in two tongues” is likely to be found also in other settings of accounting and financial intermediation, wherever a strategic player is faced with distinct audiences for different informational outlets. One example is earnings disclosure and financial accounting reports (Hirshleifer and Teoh [2003]). Another example is how firms represent their earnings and growth prospects in front of investors versus in negotiations with unions. The comparison of the information provided in both types of informational outlets can be helpful in measuring strategic components.

References

- Abarbanell, Jeffery, and Reuven Lehavy, "Biased Forecasts or Biased Earnings? The Role of Reported Earnings in Explaining Apparent Bias and Over/Underreaction in Analysts' Earnings Forecasts," *Journal of Accounting and Economics*, 36, (2003), 105-146.
- Baik, Bok and Han Yi, "Are Affiliated Analysts More Likely than Unaffiliated Analysts to Provide EPS Forecasts that Management Can Meet or Beat?" *Working Paper*, (2007).
- Barber, Brad, Reuven Lehavy, Maureen McNichols and Brett Trueman, "Buys, Holds and Sells: The Distribution of Investment Banks' Stock Ratings and the Implications for the Profitability of Analysts' Recommendations," *Journal of Accounting and Economics*, 41, (2006), 87-117.
- Barber, Brad, Reuven Lehavy and Brett Trueman, "Comparing the Stock Recommendation Performance of Investment Banks and Independent Research Firms," *Journal of Financial Economics*, forthcoming.
- Battalio, Robert H., and Richard R. Mendenhall, "Earnings Expectations, Investor Trade Size, and Anomalous Returns Around Earnings Announcements," *Journal of Financial Economics*, 77, (2005), 289-319.
- Bhattacharya, Nilabhra, Ervin L. Black, Theodore E. Christensen and Richard D. Mergenthaler, "Who Trades on Pro Forma Earnings Information?" *Accounting Review*, 82, (2007), 581-619.
- Boni, Leslie and Kent L. Womack, "Solving the Sell-Side Research Problem: Insights from Buy-Side Professionals," *Working Paper*, (2002).
- Bradley, Daniel, Brad Jordan and Jay Ritter, "The Quiet Period Goes Out With A Bang," *Journal of Finance*, 58, (2003), 1-36.
- Choi, James, David Laibson and Brigitte Madrian, "Why does the law of one price fail? An experiment on index mutual funds," *Review of Financial Studies*, forthcoming.
- Choi, James, David Laibson, Brigitte Madrian, and Andrew Metrick, "Reinforcement Learning and Savings Behavior," *Journal of Finance*, forthcoming.
- Cowen, Amanda, Boris Groyberg and Paul Healy, "Which Types of Analyst Firms are More Optimistic?" *Journal of Accounting and Economics*, 41, (2006), 119-146.
- Chan, Louis K. C., Jason Karceski and Josef Lakonishok, "Analysts' Conflict of Interest and Biases in Earnings Forecasts," *Working Paper*, (2003).
- Chen, Shuping and Dawn A. Matsumoto, "Favorable versus Unfavorable

- Recommendations: The Impact on Analyst Access to Management-Provided Information,” *Journal of Accounting Research*, 44, (2006), 657-689.
- Daniel, Kent, David Hirshleifer and Avanidhar Subrahmanyam, “Investor Psychology and Security Market under- and Overreactions,” *Journal of Finance*, 53, (1998), 1839-1885.
- Dechow, Patricia M., Amy P. Hutton and Richard G. Sloan, “The Relation Between Analysts’ Forecasts of Long-Term Earnings Growth and Stock Price Performance Following Equity Offerings,” *Contemporary Accounting Research*, 17, (2000), 1-32.
- Dugar, Amitabh and Siva Nathan, “The Effect of Investment Banking Relationships on Financial Analysts’ Earnings Forecasts and Investment Recommendations,” *Contemporary Accounting Research*, 12, (1995), 131-160.
- Ertimur, Yonca, Jayanthi Sunder and Shyam Sunder, “Measure for Measure: The Relation between Forecast Accuracy and Recommendation Profitability of Analysts,” *Journal of Accounting Research*, 45, (2007), 567-606.
- Lebate, John, “Morgan Stanley and Top Analyst Face Law Suits.” *Financial Times*, August 1 2001.
- Hirshleifer, David and Siew Hong Teoh, “Limited Attention, Information Disclosure, and Financial Reporting,” *Journal of Accounting and Economics* 36, (2003), 337-386.
- Hong, Harrison and Jeffrey D. Kubik, “Analyzing the analysts: Career concerns and biased earnings forecasts,” *Journal of Finance*, 58, (2003), 313-351.
- Hvidkjaer, Soeren, “A Trade-based Analysis of Momentum,” *mimeo*, (2001).
- International Organization of Securities Commissions, Report of the IOSCO Technical Committee on Analysts Conflicts of Interest, September 2003.
- Iskoz, Sergey, “Relative Performance and Institutional Reaction to Underwriter Analyst Recommendations,” *Working Paper*, (2002).
- Kothari, S.P. “Capital Markets Research in Accounting.” *Journal of Accounting and Economics*, 31, (2001), pp. 105-231.
- Kaszniak, Ron and Maureen McNichols, “Does Meeting Earnings Expectations Matter? Evidence from Analyst Forecast Revisions and Share Prices,” *Journal of Accounting Research*, 40, (2002), 727-759.
- Kolasinski, Adam and S. P. Kothari, “Investment Banking and Analyst Objectivity: Evidence on Analysts Affiliated with M&A Advisors.” *Journal of Financial and*

- Quantitative Analysis*, 43, (2008), pp. 817-842.
- Kothari, S.P. "Capital Markets Research in Accounting." *Journal of Accounting and Economics*, 31, (2001), pp. 105-231.
- Lee, Charles M. C., "Earnings News and Small Traders: An Intraday Analysis," *Journal of Accounting and Economics*, 15, (1992), 265-302.
- Lee, Charles M. C., and Balkrishna Radhakrishna, "Inferring Investor Behavior: Evidence from TORQ Data," *Journal of Financial Markets*, 3, (2000), 83-111.
- Lee, Charles M. C., and Mark J. Ready, "Inferring Trade Directions from Intraday Data," *Journal of Finance*, 46, (1991), 733-746.
- Lin, Hsiou-wei and Maureen F. McNichols, "Underwriting Relationships, Analysts' Earnings Forecasts and Investment Recommendations," *Journal of Accounting and Economics*, 25, (1998), 101-127.
- Ljungqvist, Alexander, Felicia Marston, Laura T. Starks, Kelsey D. Wei and Hong Yan, "Conflicts of Interest in Sell-side Research and The Moderating Role of Institutional Investors," *Journal of Finance*, 85, (2007), 420-456
- Ljungqvist, Alexander, Felicia Marston and William J. Wilhelm Jr., "Competing for Securities Underwriting Mandates: Banking Relationships and Analyst Recommendations," *Journal of Finance*, 61, (2006), 301-340.
- Loh, Roger and G. Mujtaba Mian, "Do Accurate Earnings Forecasts Facilitate Superior Investment Recommendations?" *Journal of Financial Economics*, 80, (2006), 455-483.
- Lusardi, Annamaria and Olivia Mitchell, "Baby Boomer Retirement Security: The Role of Planning, Financial Literacy, and Housing Wealth," *Journal of Monetary Economics*, 54, (2007), 205-224.
- Malmendier, Ulrike and Stefan Nagel, "Depression Babies: Do Macroeconomic Experiences Affect Risk-Taking?" *Working Paper*, (2009).
- Malmendier, Ulrike and Devin Shanthikumar, "Are Investors Naïve about Incentives?" *Journal of Financial Economics*, 85, (2007), 457-489.
- McNichols, Maureen F. and Patricia C. O'Brien "Self-Selection and Analyst Coverage," *Journal of Accounting Research*, 35, (1997), 167-199.
- Michaely, Roni and Kent L. Womack, "Conflict of Interest and the Credibility of Underwriter Analyst Recommendations," *Review of Financial Studies*, 12, (1999), 653-686.

- _____ and _____, “Brokerage Recommendations: Stylized Characteristics, Market Responses, and Biases,” in Richard Thaler, ed., *Advances in Behavioral Finance II*, forthcoming (2003).
- Mikhail, Michael B., Beverly R. Walther, Richard H. Willis, “Does Forecast Accuracy Matter to Security Analysts?,” *The Accounting Review*, 74, (1999), 185-200.
- _____, _____ and _____, “When Security Analysts Talk, Who Listens?,” *The Accounting Review*, 82, (2007), 1227-1253.
- Morgan, John and Phillip Stocken, “An Analysis of Stock Recommendations,” *Journal of Economics*, 34, (2003), 183-203.
- O’Brien, Patricia, Maureen F. McNichols and Hsiou-Wei Lin, “Analyst Impartiality and Investment Banking Relationships,” *Journal of Accounting Research*, 43, (2005), 623-650.
- Odders-White, Elizabeth R, “On the Occurrence and Consequences of Inaccurate Trade Classification,” *Journal of Financial Markets*, 3, (2000), 259-286.
- Richardson, Scott, Siew Hong Teoh and Peter Wysocki, “The Walkdown to Beatable Analyst Forecasts: The Roles of Equity Issuance and Insider Trading Incentives,” *Contemporary Accounting Research* 19, (2004), 885-924.
- Schotter, Andrew, “Decision Making in the Face of Naive Advice,” *American Economic Review, Papers & Proceedings*, (2003).
- Shanthikumar, Devin, Small Trader Reactions to Consecutive Earnings Surprises, *Working Paper* (2003).
- Teoh, Siew Hong and T. J. Wong, “Why Do New Issuers and High-Accrual Firms Underperform: The Role of Analysts’ Credulity,” *Review of Financial Studies* 15, (2002), 869-900.
- Thompson Financial, “Thompson Financial Glossary 2004, A Guide to Understanding Thompson Financial Terms and Conventions for the First Call and IBES Estimates Databases,” (2004).

TABLE I. Summary Statistics**Panel A. Recommendations and Earnings Forecasts**

Recommendations are translated into numerical values following the scheme 1=strong sell, 2=sell, 3=hold, 4=buy, 5=strong buy. Earnings Forecasts are reported in earnings-per-share dollars. The forecast sample is limited to forecasts pertaining to the closest following annual earnings announcement, and to earnings announcements that occur during the SEC mandated window of 0-90 days after the end of the relevant fiscal year. A brokerage firm is "Unaffiliated" if it has not been the lead or co-underwriter for a firm's IPO in the past 5 years or for a firm's SEO in the past 2 years. A brokerage firm is "Affiliated" if it has been a lead or co-underwriter over the same periods. A brokerage firm is "Never Affiliated" if it does not have any (lead or co-underwriter) equity or bond underwriting affiliation during the entire sample period. The sample period is 2/01/1994 to 12/31/2002.

	Recommendations								Annual Earnings Forecasts					
	Sample size	Percentage by category					Numerical translation		Sample size	Mean	Standard Deviation	Percentile		
		Strong Sell	Sell	Hold	Buy	Strong Buy	Mean	Standard Deviation				25th	50th	75th
Entire Sample														
All	112,694	1.65	2.92	36.33	33.30	25.81	3.79	0.92	460,936	1.68	1.73	0.78	1.42	2.27
Unaffiliated	106,873	1.70	2.98	36.91	33.01	25.40	3.77	0.92	453,314	1.68	1.73	0.79	1.43	2.28
Affiliated	5,821	0.86	1.68	25.55	38.60	33.31	4.02	0.86	7,622	1.37	1.79	0.60	1.11	1.78
Never Affiliated	6,250	3.76	4.32	36.70	28.35	26.86	3.70	1.03	183,212	1.72	1.76	0.80	1.45	2.32
Subsample of firms with an IPO in the past 5 years or an SEO in the past 2 years														
All	28,202	1.24	2.21	31.59	35.31	29.66	3.90	0.90	101,139	1.43	1.58	0.65	1.21	1.94
Unaffiliated	22,381	1.34	2.35	33.16	34.45	28.71	3.87	0.90	93,517	1.44	1.56	0.66	1.22	1.95
Affiliated	5,821	0.86	1.68	25.55	38.60	33.31	4.02	0.86	7,622	1.37	1.79	0.60	1.11	1.78
Never Affiliated	1,192	2.68	2.77	31.29	31.46	31.80	3.87	0.98	40,405	1.44	1.55	0.65	1.23	1.95

Panel B. Measures of Trade Reaction

	All dates			Recommendation dates			Earnings forecast dates		
	mean	median	st. dev	mean	median	st. dev	mean	median	st. dev
Number of small buy-initiated trades	49.67	15	93.38	112.41	47	153.83	105.52	44	146.09
Number of large buy-initiated trades	24.27	3	68.90	73.94	23	132.31	72.35	22	130.52
Number of small sell-initiated trades	43.25	15	80.28	95.06	42	132.64	88.05	39	124.59
Number of large sell-initiated trades	20.06	3	56.73	61.02	19	110.15	58.85	19	106.77
Total number of small buy/sell-initiated trades	92.92	31	170.90	207.47	91	281.79	193.57	84	266.31
Total number of large buy/sell-initiated trades	44.33	7	124.73	134.96	42	240.56	131.20	42	235.52
Δ (buy-sell) initiated small trades	6.42	1	33.54	17.34	5	55.74	17.46	5	52.95
Δ (buy-sell) initiated large trades	4.21	0	19.29	12.92	2	37.54	13.50	2	37.46
	<i>N 3,586,144</i>			<i>109,939</i>			<i>460,936</i>		

TABLE II. Comparison to Consensus

OLS regressions of the difference between individual analyst recommendations and consensus (average analysts recommendations over the past month) in Column (1) and of the difference between individual analyst forecasts and consensus, normalized by share price (and multiplied by 100) in Column (2), on an indicator for affiliation. In Column (2), we control for expected time to the next annual and quarterly earnings announcement (measured as days/1000). For both columns, a positive difference indicates that the analyst is optimistic relative to the consensus. For recommendations, the sample is limited to stocks with at least one recommendation in the prior month and full data availability for the prior month. For forecasts, the sample is limited to stocks with a share price of at least \$5. For both, the sample is also limited to stocks for which past affiliation is possible, i.e., stocks with an IPO in the past 5 years or SEO in the past 2 years. We include fixed effects for year, month and day-of-week. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and within-date correlation.

	Recommendations (1)	Annual Earnings Forecasts (2)
Affiliated	0.0602 (0.0070)	-0.0324 (0.0174)
Expected time to annual earnings announcement		0.7260 (0.0818)
Expected time to quarterly earnings announcement		-0.0489 (0.1219)
Fixed Effects for year, month, and day-of-week	Yes	Yes
Number of Observations	28,202	92,219
R ²	0.0035	0.0070

TABLE III. Timing**Panel A. Sample Statistics**

Mean (median) number of days until new recommendation or forecast (same stock + analyst)								
Recommendations	Conditional on Level of Recommendation						Relative to Update	
	Overall	Strong			Strong		Before	Before
		Sell	Sell	Hold	Buy	Buy	Increase	Decrease
Unaffiliated	322.7 (191)	143.7 (81)	176.3 (101)	326.8 (184)	312.2 (184)	349.9 (223)	296.5 (163)	342.0 (212)
Affiliated	370.9 (234)	118.0 (57)	82.8 (57)	307.9 (195)	363.7 (235)	431.1 (274)	304.8 (183)	410.2 (269)
Earnings Forecasts	Relative to Consensus						Relative to Update	
	Overall	Below	Equal to	Above		Before	Before	
		Increase	Decrease	Increase	Decrease	Increase	Decrease	
Unaffiliated	64.2 (55)	61.6 (51)	89.2 (74)	64.8 (56)	64.8 (56)	64.7 (56)	63.7 (53)	
Affiliated	65.2 (56)	60.1 (50)	89.0 (76)	67.4 (59)	67.4 (59)	64.8 (58)	65.5 (54)	

Sample Period is 2/01/1994 to 12/31/2002. The sample is limited to stocks for which past affiliation is possible, i.e., stocks with an IPO in the past 5 years or SEO in the past 2 years.

Panel B. Regression Analysis

OLS regressions of the number of days until the next recommendation or forecasts by the same analyst for the same stock (Columns 1 and 3) and of recommendation level minus consensus (average over the past month, Column 2) on recommendation or forecast controls and their interactions with affiliation dummies. The sample excludes reiterations and is limited to stocks for which past affiliation is possible, i.e., stocks with an IPO in the past 5 years or SEO in the past 2 years. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and within-date correlation.

	Days until	Diff. to		Days until
	update	consensus		update
	(1)	(2)		(3)
Strong Sell, Sell, Hold	308.77 (7.57)	-0.40 (0.01)	Above consensus	64.83 (0.47)
Buy	312.22 (6.40)	0.00 (0.01)	Equal to consensus	89.19 (1.31)
Strong Buy	349.94 (6.97)	0.38 (0.01)	Below consensus	61.57 (0.45)
(Strong Sell, Sell, Hold) *(Affiliation)	-20.25 (15.39)	0.13 (0.02)	(Above consensus) *(Affiliation)	2.61 (1.06)
(Buy) *(Affiliation)	51.51 (12.65)	-0.01 (0.01)	(Equal to consensus) *(Affiliation)	-0.18 (3.68)
(Strong Buy) *(Affiliation)	81.17 (15.33)	-0.07 (0.02)	(Below consensus) *(Affiliation)	-1.47 (0.95)
Number of Observations	14,911	14,911	Number of Observations	71,119
R ²	0.43	0.32	R ²	0.63

TABLE IV. Trade Reaction: Regression Results

OLS regressions of trade reaction on recommendation and forecast update values. Trade reaction is measured by abnormal trade imbalance. Large traders represent trades of at least \$50,000; small traders represent trades of less than \$20,000. Recommendation update is the difference between a recommendation (1=strong sell, 2=sell, 3=hold, 4=buy and 5=strong buy) and the prior recommendation by the same analyst for the same firm. Forecast update is the difference between a forecast and the prior forecast by the same analyst for the same firm, normalized by share price. The sample period is 2/01/94-12/31/02. The sample is limited to stocks for which past affiliation is possible, i.e., stocks with an IPO in the past 5 years or SEO in the past 2 years. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and within-day correlation.

		Recommendations			Annual Earnings Forecasts		
		Small Traders	Large Traders	Difference (S-L)	Small Traders	Large Traders	Difference (S-L)
Unaffiliated	Update	0.0650 (0.0075)	0.0507 (0.0068)	0.0144 (0.0101)	-0.0997 (0.2497)	0.9771 (0.1820)	-1.0768 (0.3090)
	Constant	0.0630 (0.0105)	0.0080 (0.0093)	0.0549 (0.0140)	0.0844 (0.0076)	0.0127 (0.0070)	0.0716 (0.0104)
	<i>N</i>	13,644	13,644		62,144	62,144	
	<i>R</i> ²	0.0065	0.0044		0.0000	0.0008	
Affiliated	Update	0.0740 (0.0146)	0.0426 (0.0136)	0.0314 (0.0200)	-0.3832 (0.4851)	0.7197 (0.4834)	-1.1030 (0.6849)
	Constant	0.0807 (0.0165)	0.0231 (0.0167)	0.0576 (0.0235)	0.0972 (0.0152)	0.0124 (0.0138)	0.0847 (0.0205)
	<i>N</i>	3,616	3,616		5,070	5,070	
	<i>R</i> ²	0.0070	0.0026		0.0001	0.0004	

TABLE V. Relationship between Forecast Optimism and Recommendation Optimism

OLS regressions of forecast optimism on recommendation optimism, affiliation, and interaction. Forecast optimism is defined as the difference between an annual earnings forecast and the consensus, divided by the stock price on the forecast date (and multiplied by 100). Recommendation Optimism is the difference between a recommendation and the consensus for the same stock (over the past month) at the time of the earnings forecast. Affiliation is a binary variable and equal to 1 if the analyst's brokerage house is affiliated with an investment bank with a past SEO- or IPO- (co- or lead-)underwriting relationship. Panel A displays results for the full sample. Panel B displays results for the subsample of analysts who have at least one affiliated forecast or recommendation outstanding and at least one unaffiliated forecast or recommendation outstanding. The sample is limited to earnings forecasts within 80 days before the earnings announcement and to stocks with prices of at least \$5 and for which past affiliation is possible, i.e., stocks with an IPO in the past 5 years or SEO in the past 2 years. Standard errors (in parentheses) are robust to heteroskedasticity and arbitrary within-analyst correlation.

Panel A. All Analysts

	Whole Sample	Unaffiliated	Affiliated	Whole Sample
Recommendation Optimism	0.00240	0.01290	-0.14270	0.01200
	(0.01480)	(0.01480)	(0.07630)	(0.01480)
Affiliation				-0.03320
				(0.05250)
Affiliation*(Recommendation Optimism)				-0.13630
				(0.07180)
Fixed Effects for year, month and day-of-week	Yes	Yes	Yes	Yes
Number of Observations	7,080	6,640	440	7,080
R ²	0.0235	0.0227	0.0775	0.0243

Panel B. Analysts who are both affiliated and unaffiliated

	Whole Sample	Unaffiliated	Affiliated	Whole Sample
Recommendation Optimism	-0.04070	0.03800	-0.14520	0.04270
	(0.04970)	(0.05930)	(0.07680)	(0.05950)
Affiliation				-0.09980
				(0.06940)
Affiliation*(Recommendation Optimism)				-0.17680
				(0.09200)
Fixed Effects for year, month and day-of-week	Yes	Yes	Yes	Yes
Number of Observations	995	558	437	995
R ²	0.0619	0.0971	0.0779	0.0714

TABLE VI. Earnings Forecasts: Positive Forecast Error

Logit model, where the dependent variable takes the value of 1 if the earnings forecast is greater than the earnings realization. The sample is limited to the last forecast of a given analyst for a particular firm's fiscal period. Expected time to annual (quarterly) earnings announcements is based on the dates of the previous year's earnings announcements. The sample period is 02/01/1994 to 12/31/2002 for the "full period" estimations and 02/01/1994 to 7/31/2001 for the "pre-scandal period." The sample is also limited to stocks for which past affiliation is possible, i.e., stocks with an IPO in the past 5 years or SEO in the past 2 years. Standard errors (in parentheses) are robust to arbitrary heteroskedasticity and within-analyst correlation.

	Full Period		Pre-Scandal Period	
	(1)	(2)	(3)	(4)
Affiliated	-0.0724 (0.0496)	-0.0592 (0.0480)	-0.1013 (0.0566)	-0.0899 (0.0556)
Expected time to annual earnings announcement [in thousandths]	0.0030 (0.0001)	0.0030 (0.0001)	0.0031 (0.0001)	0.0031 (0.0002)
Expected time to next quarterly announcement [in thousandths]	-0.0008 (0.0003)	-0.0008 (0.0003)	-0.0012 (0.0004)	-0.0011 (0.0003)
Forecast optimism relative to consensus, normalized by share price		-1.8656 (0.4913)		-1.2917 (0.6802)
Constant	-0.8951 (0.0285)	-0.9140 (0.0277)	-0.9222 (0.0313)	-0.9375 (0.0307)
Number of Observations	28,602	27,901	23,151	22,579
χ^2	497	471	430	402
Pseudo R ²	0.0141	0.0145	0.0154	0.0154

TABLE VII. Measures of Strategic Distortion

The sample consists of all recent equity issuers (stocks with an IPO in the past 5 years or SEO in the past 2 years). Recommendation optimism is defined as the analysts' recommendation minus the consensus recommendation as of that day. Scaled forecast optimism is earnings forecast optimism, defined as earnings per share forecast minus consensus, normalized by share price, multiplied by 100 and winsorized at the 1% tails. Recommendation is the recommendation level on a scale of 1-5. "Forecast-implied recommendation" is the recommendation implied by using the analysts' earnings per share and long term growth forecasts with current stock price as of the recommendation date to determine the appropriate recommendation using the price-earnings-growth (PEG) model. Panel A displays statistics for the full sample. Panel B displays statistics for the subsample of analysts who have at least one affiliated forecast or recommendation outstanding and at least one unaffiliated forecast or recommendation outstanding. Panel C displays statistics for the subsample of all analysts who are listed in Institutional Investor Magazine's October listing of top sell-side

Panel A. All analysts

	obs.	mean	median	st. dev.	25 th % ^{ile}	50 th % ^{ile}	75 th % ^{ile}	% neg.	% pos.
Measure 1: Recommendation optimism minus scaled forecast optimism									
All analysts	54,449	0.25	0.06	1.16	-0.42	0.06	0.92	23.08	76.08
Unaffiliated analysts	50,838	0.23	0.06	1.16	-0.43	0.06	0.91	23.54	75.64
Affiliated analysts	3,611	0.42	0.17	1.14	-0.19	0.17	1.00	17.47	81.51
p-value for difference in means, affiliated vs. unaffiliated: 0.00%									
Measure 2: Recommendation minus forecast-implied recommendation									
All analysts	71,713	0.08	0	1.70	-1	0	1	29.15	51.88
Unaffiliated analysts	66,368	0.07	0	1.71	-1	0	1	29.39	51.98
Affiliated analysts	5,345	0.16	0	1.58	-1	0	1	26.09	50.69
p-value for difference in means, affiliated vs. unaffiliated: 0.01%									

Panel B. Analysts who are both affiliated and unaffiliated

	obs.	mean	median	st. dev.	25 th % ^{ile}	50 th % ^{ile}	75 th % ^{ile}	%neg.	%pos.
Measure 1: Recommendation optimism minus scaled forecast optimism									
All (aff. and unaff.) analysts	7,946	0.31	0.10	1.15	-0.33	0.10	0.95	21.81	77.32
Unaffiliated analysts	4,357	0.22	0.05	1.15	-0.47	0.05	0.89	26.13	73.15
Affiliated analysts	3,589	0.42	0.16	1.15	-0.19	0.16	1.00	17.54	81.43
p-value for difference in means, affiliated vs. unaffiliated: 0.00%									
Measure 2: Recommendation minus forecast-implied recommendation									
All (aff. and unaff.) analysts	10,960	0.03	0	1.58	-1	0	1	29.12	47.52
Unaffiliated analysts	5,664	-0.10	0	1.58	-1	0	1	32.27	44.25
Affiliated analysts	5,296	0.16	0	1.58	-1	0	1	26.02	50.74
p-value for difference in means, affiliated vs. unaffiliated: 0.00%									

TABLE VIII. Within-Analyst Persistence of Strategic Distortion

The sample consists of all recent equity issuers (stocks with an IPO in the past 5 years or SEO in the past 2 years). The two distortion measures are defined in Table VII. Strategic distortion is measured at the time of forecast issuance. (Un-)Affiliated analysts is the subsample of forecast/recommendations issued by (un-)affiliated analysts. Same analyst, same stock indicates the probability of strategic distortion of the next forecast/recommendation pair by the same analyst for the same stock. Same analyst, any stock indicates the probability of strategic distortion for the subsequent forecast/recommendation by the same analyst, regardless of the stock. Same analyst, different stock indicates the probability of strategic distortion for a different stock by the same analyst. In the next two rows, "Same analyst, any stock" is split into subsamples depending on whether the subsequent forecast/recommendation pair was affiliated or not. The last two rows indicate the probability of strategic distortion for the next (not necessarily subsequent) forecast/recommendation pair that is affiliated or unaffiliated.

Measure 1: Recommendation optimism minus scaled forecast optimism

Probabilities of positive distortion (in %)	From					
	Whole sample		Affiliated analysts		Unaffiliated analysts	
	Strategically distorted (measure 1 > 0)?					
	yes	no	yes	no	yes	no
Same analyst, same stock	83.52	50.42				
Same analyst, any stock	79.17	64.78				
Same analyst, different stock	78.45	66.92				
Same analyst – next forecast is affiliated			85.74	71.17	82.32	77.40
Same analyst – next forecast is unaffiliated			77.64	70.33	79.13	64.53
Same analyst – next affiliated forecast			84.9	68.53	82.30	75.72
Same analyst – next unaffiliated forecast			77.62	69.94	79.14	64.50

Measure 2: Recommendation minus forecast-implied recommendation

Probabilities of positive distortion (in %)	From					
	Whole sample		Affiliated analysts		Unaffiliated analysts	
	Strategically distorted (measure 2 > 0)?					
	yes	no	yes	no	yes	no
Same analyst, same stock	88.96	9.28				
Same analyst, any stock	71.91	30.05				
Same analyst, different stock	70	32.17				
Same analyst – next forecast is affiliated			75.68	27.27	63.79	37.24
Same analyst – next forecast is unaffiliated			60.54	34.63	72.15	29.89
Same analyst – next affiliated forecast			77.47	21.85	59.90	37.58
Same analyst – next unaffiliated forecast			61.37	34.53	72.14	29.91

Figure 1. Distortion Metrics

The left column illustrates the construction of the first metric of strategic distortion, recommendation optimism minus scaled forecast optimism. The top figure displays the distribution of recommendation optimism, defined as recommendation minus consensus recommendation as of that day. The middle figure displays earnings forecast optimism, defined as earnings-per-share forecast minus consensus, normalized by share price. Forecast optimism is then multiplied by 100 and winsorized at the 1% tails. The bottom figure displays the difference between recommendation optimism and scaled, winsorized, forecast optimism. The right column illustrates the construction of the second metric of strategic distortion, recommendation minus forecast-implied recommendation. The top figure displays recommendation levels. The middle figure displays recommendation levels implied by analysts' earnings-per-share and long-term growth forecasts using the price-earnings-growth (PEG) model. The bottom figure displays the difference between recommendations and implied recommendations.

Recommendation optimism minus scaled forecast optimism

Recommendation minus forecast-implied recommendation

