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Source: *The Journal of Finance*, Vol. 60, No. 2 (Apr., 2005), pp. 673-717
Published by: Blackwell Publishing for the American Finance Association
Stable URL: http://www.jstor.org/stable/3694764
Accessed: 23/11/2009 12:30

THE JOURNAL OF FINANCE • VOL. LX, NO. 2 • APRIL 2005

Trade Generation, Reputation, and Sell-Side Analysts

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ABSTRACT

This paper examines the trade-generation and reputation-building incentives facing sell-side analysts. Using a unique data set I demonstrate that optimistic analysts generate more trade for their brokerage firms, as do high reputation analysts. I also find that accurate analysts generate higher reputations. The analyst therefore faces a conflict between telling the truth to build her reputation versus misleading investors via optimistic forecasts to generate short-term increases in trading commissions. In equilibrium I show forecast optimism can exist, even when investment-banking affiliations are removed. The conclusions may have important policy implications given recent changes in the institutional structure of the brokerage industry.

SIGNIFICANT MEDIA, REGULATORY, AND ACADEMIC ATTENTION has recently been focused on the conflicts of interest generated by the relationship between sell-side analysts and investment-banking departments. One outcome of this controversy was a settlement between U.S. regulators and 10 top investment banks requiring "a clear separation of the research and investment-banking divisions at (brokerage) firms".[1] A key assumption underlying this settlement is that splitting analyst research and trading away from investment banking significantly reduces conflicts of interest affecting analyst research, leading presumably to unbiased earnings estimates and better outcomes for brokerage clients.

However, with the introduction of such an institutional structure, the incentive for sell-side analysts to generate investment-banking business is simply replaced by the incentive to generate trading commissions. Indeed, such an incentive has already long existed in the previous institutional structure, but has not been examined closely in the academic literature to date due to a lack of available data. This paper provides strong empirical evidence that optimistic

*Andrew Jackson is at Barclays Global Investors, Sydney, Australia. This paper is a modified version of a chapter of my doctoral thesis completed at London Business School. I thank Harjoat Bhamra, Richard Brealey, Denis Gromb, Paul Irvine, Terrance Odean, Marco Ottaviani, Stefano Rossi, Michael Ulm, Hongjun Yan, Robert Stambaugh (the editor), an anonymous referee, my BGI colleagues, seminar participants at London Business School and UNSW, and especially my PhD supervisor Timothy Johnson for valuable comments and suggestions. Jennifer Jackson provided brilliant editing assistance. I thank Nick Coles for providing the extensive survey data used in this research and an anonymous broker and I/B/E/S for making their data available for academic use. I am responsible for any errors.

[1] For details of the U.S. settlement, see http://www.oag.state.ny.us/press/statements/global_resolution.html.

analysts generate higher trading volumes for their firm, providing an incentive for analysts to upwardly bias their forecasts and recommendations.

This incentive is limited in reality by analysts' concerns about their reputations. Since analysts interact with investors repeatedly, opportunistic behavior may be curtailed by the threat of negative repercussions in the future. In this situation, the analyst must trade off the short-term incentive to lie and generate more trade against the long-term gains from building a good reputation. I present empirical evidence that analysts with better reputations generate significantly higher future trading volume for the brokers they work for. Thus, analysts have a strong economic incentive to develop their reputations. I also show empirically that the market updates analyst reputations in a consistent way, with more accurate forecasters attaining higher end-of-period reputations.

A second aspect of the debate concerning analysts' conflicts of interest is differing beliefs about the rationality of investors who receive analyst research. Several financial economists have questioned the appropriateness of significant regulatory intervention in analyst research production. For example, Kent Womack states that "Just as consumers know to be somewhat skeptical of the commercials they see on television, so do professional investors know how to de-bias information they receive from analysts."[2] For convenience throughout the paper I label this point of view as the neoclassical view.

An alternative view, which I label the Spitzer view,[3] is that investors (especially smaller investors) are unable to correctly de-bias analyst research and as a result are systematically misled by optimistic forecasts. For example, the *Wall Street Journal* reports that brokers were "hyping stocks to win lucrative investment-banking work from corporate clients, and were misleading investors in the process" (Gasparino (2002)). This view asserts that investors *are* likely to be fooled by analyst hype and therefore need some form of regulatory protection.

At first glance, my empirical finding that optimistic analysts generate more trade appears to provide strong support for the Spitzer position. Indeed, if analysts *were* fooling investors by issuing spurious buy recommendations and optimistic forecasts, this empirical result is exactly what we would expect to find (given the heavily right-skewed distribution of broker recommendations). However, my second and third empirical findings, that investors pay more attention to high-reputation analysts and update reputations based on past forecasting performance, are more consistent with the neoclassical position.

To reconcile these apparently conflicting results, I develop a simple model describing the interaction between analysts and investors. Using this model, I show that my three empirical findings can be generated inside a fully rational

[2] Source: http://www.upenn.edu/researchatpenn/article.php?sol&soc, published November 6, 2002.

[3] Elliot Spitzer (New York State Attorney General) led the high-profile investigations into conflicts of interest at Wall Street investment firms in 2001. These investigations lead to the settlement between banks and regulators that required the separation of research and banking.

framework after allowing for the presence of asymmetric information about an analyst's motivations. The model also generates two further comparative statics predictions, namely that consensus optimism is higher when short-sales constraints are higher and when dispersion is higher. These predictions are subsequently supported by the data.

Using this model, I am also able to impose a particular type of investor irrationality consistent with the Spitzer view, namely that a proportion of investors naively believe that analysts' forecasts and recommendations are always truthful. Using this modification, we can directly test the neoclassical versus Spitzer views. The empirical results, showing that cross-sectional optimism levels do not increase as the percentage of small investors increases, support the predictions of the neoclassical position, allowing us to distinguish somewhat between the two competing views.

This paper adds to the empirical literature on the trade-generation incentives facing sell-side analysts. Given the current settlement requiring brokerage firms to be split in two, these incentives are likely to become significantly more important going forward. In a policy sense, my empirical results suggest that optimistically biased forecasts are unlikely to disappear after the proposed changes. However, measures that enable investors to cheaply monitor past analyst forecasting performance[4] may be an effective tool for ameliorating this effect. Such policies make the analyst's reputation more transparent and increase the implicit penalty for opportunistic behavior. Measures to reduce short-sales constraints facing investors would also decrease the extent of the problem.

In a broader sense, the paper adds to the economics literature on the empirical importance of reputation formation. I show empirically that reputation matters in the market for professional advice. I also add to the behavioral/rationalist debate by demonstrating how a simple model with rational investors and asymmetric information can be applied to generate apparently behavioral phenomenon. My empirical results do not support the conclusion that investors are stupid and need to be protected, but do suggest that moves to decrease the cost of acquiring information about analyst quality would be helpful.

The paper is structured as follows. Section I discusses some related literature. Section II describes the data sample and defines variables used in the empirical analysis. Section III contains the central empirical results of this study, examining the interaction between trade generation, reputation, and optimism. Section IV develops a simple model explaining how these results can be generated within a simple rational framework. Section V tests three supplementary predictions from the model. Section VI concludes.

[4] For example, the U.S. settlement requires firms to make "certain analyses generated by an investment house... public within 90 days after the conclusion of each quarter. This will enable investors to compare and evaluate the performance of analysts from different firms and permit the market to generate objective rankings." Source: http://www.oag.state.ny.us/press/statements/global_resolution.html.

I. Related Literature

This paper is related to existing research on institutional incentives facing sell-side analysts and also draws on literature examining reputation effects in repeated games. This section presents a brief review of the literature. The time-starved reader can, however, jump straight to the empirical results in Section III with little loss of continuity.

A. Sell-Side Analyst Behavior

Sell-side analyst behavior has been examined extensively over the last two decades. Analysts' forecasts appear to contain valuable private information (Dimson and Marsh (1984), Womack (1996)), despite many authors documenting that earnings forecasts appear to be upwardly biased on average (e.g., O'Brien (1988), Lys and Sohn (1990), Brown (1993), Dugar and Nathan (1995)).[5] Optimism bias is generally attributed to analysts' responses to institutional incentives, including investment banking (Lin and McNichols (1998), Michaely and Womack (1999)), management relations (Francis and Philbrick (1993), Das, Levine, and Sivaramakrishnan (1998), Lim (2001)), and trade generation. This paper focuses on the latter channel, whose importance is likely to increase following the separation of investment banking and research induced by changes in exchange rules (NYSE Rule 472 and NASD Rule 2210) and by recent regulatory action (Spitzer (2002)).

Several authors have previously examined the incentives for analysts to generate trade. Hayes (1998) models an analyst's information production decision in the presence of trade-generation incentives. Irvine (2003) finds using Canadian data in 1994 that in event time, optimistic recommendations generate higher own-broker trading volume while optimistic earnings forecasts do not. Aitken, Muthuswamy, and Wong (2001) find using Australian data that buy recommendations lead to a higher market share in an event window around announcement, while sell recommendations do not. My paper verifies the optimism/market-share result using an extensive data set, while carefully controlling for investment-banking relationships and analyst reputation variables. More importantly, this paper extends this stream of literature by examining the trade-off an analyst faces between generating more trade today versus engaging in reputation formation that enables generation of more trade in the future.

Analyst reputation effects have been examined previously using data from institutional surveys that rank sell-side analysts. Stickel (1992) finds that the forecasts of top-ranked (All-American) analysts are more accurate and have larger return impacts than other forecasts. Analysts also have strong career-concern incentives to develop their reputations (Leone and Wu (2002), Hong and Kubik (2003)) given that promotions, job separations, and compensation

[5] Several recent authors challenge the unconditional optimism result, for exampleat-penn/article.php?sol&soc, Keane and Runkle (1998) and Gu and Wu (2003).

are often dependent on survey rankings. My work extends this literature by demonstrating a clear empirical link between analyst reputation (ranking) and future own-broker trading volume. To my knowledge, this link has not been established in previous research.

B. Reputation and Repeated Games

It is well known in game theory that the presence of repeated interaction between agents can act as an important disciplining device in preventing opportunistic behavior.[6] Under certain conditions, agents have incentives to engage in reputation building and to take actions that would not be rational in a one-shot game. This concept has previously been applied to finance in a broad number of contexts.

Fama (1980) argues that agency problems between managers and shareholders are likely to be minimized due to managers' concerns for their reputations in the labor market. Reputation has also been applied in alleviating agency problems associated with sovereign debt (Eaton and Gersovitz (1981)), risky corporate debt (John and Nachman (1985), Diamond (1989)), and outside equity (Gomes (2000)). Benabou and Laroque (1992) also apply the idea to model market manipulation by newsletter writers.

Reputation effects have also been examined in experimental settings that are quite relevant to the present setting. DeJong et al. (1985) find evidence of reputation building over several periods of trade in simulated markets. They find that the ability of agents to audit ex post the actions of other agents reduces the level of cheating, especially when audit results are publicly disclosed. In our setting, the ability of investors to cheaply monitor the past recommendations of analysts is important. Several of the policy measures recently introduced encourage analysts to transparently report information on the success of past recommendations.[7] These measures are likely to strengthen the reputational considerations of analysts.

This paper applies the basic insights from research on reputation effects to a sell-side analyst setting in order to assess how an analyst's desire to generate a reputation for forecasting ability can reduce her level of opportunistic behavior.

II. Data Description and Variable Definitions

This study uses extensive data from the Australian equity market over the period from January 1992 to December 2002. Only stocks included in the main benchmark index (the All Ordinaries index to March 2000 and the ASX300 subsequently) are used, giving between 250 and 350 stocks in each weekly

[6] For seminal papers on reputation in finitely repeated games see Kreps and Wilson (1982) and Milgrom and Roberts (1982).

[7] See Boni and Womack (2002) for a description and discussion of the new measures introduced by the NYSE and Nasdaq.

cross section, and capturing around 88% of total market capitalization. Non-index stocks are excluded due to extreme illiquidity and to ensure that the results are not driven by an economically insignificant section of the market.

The Australian market represents an ideal laboratory in which to test hypotheses on trade-generation and reputation. The major brokerage firms are similar to those present in U.S. and European markets and the equity market is highly developed. In addition, detailed data on brokerage trading volumes are available via the fully electronic market system, SEATS. Such detailed data are not currently available to academics over such a long period, to my knowledge, in other equity markets.

In the empirical analysis, two large unique data sets describing broker market shares of trading volume and analyst rankings are combined with the I/B/E/S and SDC Platinum databases. I briefly describe the four data sets below.

A. Broker Market Share Data

Detailed data on the trades generated by 23 institutional brokerage firms was collected for the period January 1992 to December 2002 for all stocks in the Australian market. The data set contains weekly information on the aggregate trades of all clients of each broker. The information available is the number of trades, value traded, and average price of all buy and sell trades executed by each broker during the week, for each stock. The data are proprietary and were supplied by an Australian broker. The information used in this study is observable in real time on a trade-by-trade basis by some market participants (brokers) but is not available to investors in general.

Table I presents summary statistics describing the data set, showing the overall average market share of the 23 brokers over the full period and the number of years of data available for each broker. Table II reveals that market share is strongly concentrated in the top 10 brokers; however, within these 10, the market shares are relatively evenly distributed.

B. Analyst Reputation Information

Analyst reputation was measured using rankings from the leading Australian analyst survey, the East Coles Survey. This is the Australian equivalent of the U.S. Institutional Investor survey and is conducted over a large number of buy-side institutions once each year.[8] Survey respondents rate analysts on the quality of research, level of service, and overall general satisfaction. Survey ranking data were available annually from 1994 to 2002. The data available

[8] Results of the survey are published in July each year. Rankings in the survey are a weighted average of institutional responses, with the weights based on the assets under management of the respondent. Equal weighted rankings are also available, but are not used in this study. Analyst rankings from these surveys were hand-matched each year to the analyst and broker code in the I/B/E/S database using the confidential broker translation file kindly provided by I/B/E/S.

Table I

Summary Statistics

This table presents summary statistics for the 23 brokers in the sample. Broker names are excluded due to confidentiality constraints. The first column contains the number of years of market share data available for the sample; the second column the number of years for which the broker supplies estimates to I/B/E/S. The third column shows the number of trades done by that broker. The fourth is the average market share over the years available. The fifth column counts the number of times the manager acted as lead manager in an IPO for a stock that was included in the index during the sample period. The sixth column counts comanager participation in IPOs. The last two columns count lead and comanager participation for SEOs.

Broker #	Full Years in Market Share Sample	Full Years in IBES Sample	Number of Trades by Broker	Average Annual Market Share (%)	Lead Manager IPO	Comanager IPO	Lead Manager SEO	Comanager SEO
1	10	10	10,448,204	8.3	31	13	103	5
2	10	10	10,355,971	11.9	26	8	86	5
3	10	10	6,588,775	7.9	33	12	206	5
4	10	10	6,116,852	8.5	22	6	48	3
5	10	10	5,947,764	13.5	15	8	35	2
6	10	10	5,741,376	8.2	23	18	31	4
7	10	10	5,449,647	8.8	19	23	45	7
8	10	10	5,354,301	7.7	12	8	51	5
9	6	10	4,898,021	7.3	17	1	20	2
10	10	5	3,118,767	1.2	13	7	22	3
11	4	4	2,048,482	1.0	1	1	2	1
12	10	5	1,338,699	1.3	8	2	21	2
13	8	8	1,321,021	2.0	8	0	13	0
14	6	4	1,266,551	1.7	6	5	28	1
15	10	4	1,257,281	0.3	0	1	5	0
16	10	5	1,155,168	0.2	5	4	15	0
17	10	6	1,079,777	0.2	2	10	38	5
18	10	7	959,765	0.2	2	6	6	0
19	10	10	824,243	2.2	4	5	21	1
20	3	3	688,263	0.4	0	2	0	0
21	10	5	337,776	0.1	1	12	15	0
22	10	2	157,428	0.0	0	0	0	0
23	6	3	145,870	0.1	0	2	1	0

from the East Coles Survey has a significant advantage over that from the Institutional Investor surveys, in that it provides significantly more detailed ranking information on analysts. For each industry (and in some cases stocks) I am able to observe the ranking for *every* analyst in that sector (e.g., ranking analysts down to the 56th ranked small-cap analyst in 2000). This contrasts with the Institutional Investor survey where only the top three All-American analysts (and up to four runners up) are observable for each sector. The extra information allows significantly more precise measurement of reputation than has previously been available. Table III presents summary statistics showing the number of analysts rated in each sector or stock. Industry definitions change

Table II
Market Concentration in Trading Volume

This table presents summary statistics describing market concentration in the Australian broking market. The percentage of total volume accounted for by the top 5, the top 10, and all 23 broking firms is calculated annually across all stocks.

	Percentage of Market Share Accounted for by:		
Year	Top 5 Brokers (%)	Top 10 Brokers (%)	All 23 Brokers (%)
1993	59.6	81.4	85.1
1994	60.5	81.3	84.7
1995	60.9	81.0	83.9
1996	59.4	86.8	93.8
1997	53.4	86.0	95.2
1998	51.5	86.3	95.1
1999	51.1	85.6	93.9
2000	48.0	82.1	90.4
2001	50.1	82.6	90.6
2002	49.5	82.1	89.6
Average	54.4	83.5	90.2

over time, and the same analyst may appear in several industry categories with a different rating. For the empirical tests, if an analyst is ranked in two sectors, I use the rating of the analyst appropriate to the stock in question.

C. Investment-Banking Affiliations

Data on investment-banking affiliations were obtained from the SDC Platinum Global New Issues database. For each IPO and SEO deal, the lead and comanager was identified and hand-matched to the brokers in my sample. Summary statistics for lead and comanager status for each of the brokers are given in Table I. Investment-banking affiliation status is a particularly important control variable in this research since the link between optimism and affiliation is well known from previous research (Michaely and Womack (1999), Lin and McNichols (1998)).

D. Analyst Forecast Information

Analyst earnings forecasts and recommendations were obtained from the detail history I/B/E/S database from 1992 to 2002. The confidential broker translation files were used to link the I/B/E/S data to the turnover data for my sampled brokers. Earnings forecasts were available for 87.6% of the stocks in the average cross section. The average level of analyst coverage was 14.3 for top 20 stocks, 11.8 for stocks ranked 21–50, 8.4 for stocks ranked 51–100, and 4.1 for Ex-100 stocks. Recommendation data were also obtained from I/B/E/S, but were only available for a subset of the stocks in the sample and for a reduced time period (1994 to 2002). The I/B/E/S forecast data were used to calculate several measures of accuracy, optimism, and timeliness for each analyst–stock pair in

Table III

Survey Data—Number of Rated Analysts per Sector by Year

This table contains summary statistics describing the analyst survey data. The table lists the number of rated analysts in each sector or stock for each year of the sample. Individual stock rankings are available for stocks with the following tickers: BHP, BTR, RIO, MIM, PDP, SRP, and WMC.

Sector	1994	1995	1996	1997	1998	1999	2000	2001	2002	Total
Alcohol	13									13
Alcohol & tobacco				13	16	19	11	17	18	94
Banks	14	15	15	16	19	19	20	21	24	163
Base metals							24	25		49
BHP	13	11	12	14	11	12				73
Brewing	14	13								27
BTR	12	11								23
Building materials	12	13	12	14	13	12	14	12	11	113
Chemicals	12	11	11	10	13	19				76
Chem & Healthcare							18			18
Commodities	12	12	13	16	16	13	17	21	15	135
Developers & contractors	9	11	9	11	8	9	15	14	14	100
Diversified financials									15	15
Diversified industrials				19	18	19	19	15	13	103
Diversified resources								20	22	42
Energy				21	13	14	14	13	15	90
Engineering	9	12	10	9	17	16				73
Food & household	14	17	18	17	19	15	15	14	13	142
Gold	20	27	38	34	25	21	20	16	17	218
Health care & biotech								15	17	32
Hotels									10	10
Infrastructure & utilities					12	18	14	18	13	75
Insurance	10	9	9	14	15	16	17	15	16	121
Investment & financials								18		18
Media	16	17	17	19	15	17	26	25	27	179
Metals & mining									22	22
MIM	19	14	11	25	27	20				116
Oil & gas	18	18	13							49
Paper & packaging	16	19	15	15	16	16	13	11	13	134
PDP	11	14	14	11	14	14				78
Property trusts	19	26	24	36	32	37	35	23	28	260
Retail	15	14	15	16	16	15	13	15	14	133
RIO	17	17	15	14	14	14				91
Small cap	23	44	48	52	45	38	56	34	29	369
Solid fuels	10	10	14							34
SRP	13	13	10	12	14	15				77
Technology							40	27		67
Telecoms		17	13	14	16	18	25	30	25	158
Tobacco		13	10							23
Tourism & leisure		11	9	15	12	13	10	10		80
Transport	12	14	12	15	16	12	11	12	16	120
Wine		13	10							23
WMC	15	16	16	15	15	12				89
Total	368	452	413	467	467	463	447	441	407	3,925

the data. Each measure calculates the relative performance of the analyst versus the other analysts covering the same stock in order to control for changes in the information environment over time for a given stock. The measures are described in greater detail below.

D.1. Measuring Analyst Accuracy

Analyst accuracy has traditionally been measured as the absolute forecast error, scaled by current or lagged price (e.g., Brown et al. (1987, p. 167)). The forecast used to evaluate accuracy for analyst i for firm j in year t is generally taken to be the most recent forecast made by the analyst prior to some fixed date a month or several months before the end of the fiscal year.

$$AE_{i,j,t} = |F_{i,j,t} - A_{j,t}|/P_{j,t-k}, \tag{1}$$

where $F_{i,j,t}$ is the most recent forecast prior to cutoff date; $A_{j,t}$ is actual earnings per share for firm j; and $P_{j,t-k}$ is stock price k periods prior to announcement.

When comparing analyst forecast errors across different firms, several authors (e.g., Clement (1999), Hong and Kubik (2003)) note that we should adjust our measure to account for the fact that the information environment may differ across firms. For example, a regulated utility company may have earnings that are easier to forecast than an airline's. Alternatively, some firms may engage in analyst guidance or earnings management while others may not.

To correct for differences in information environments, two alternative measures have been proposed. The first, from Clement (1999), subtracts the average absolute error for all analysts covering the stock in that year.

$$MAE_{i,j,t} = AE_{i,j,t} - \mathrm{Avg}(AE_{i,j,t}), \tag{2}$$

where $\mathrm{Avg}(AE_{i,j,t})$ is average absolute error for all analysts covering the firm.

The second method, from Hong and Kubik (2003), is to rank analysts based on their absolute forecast error in a given year, then scale analysts' rankings between one (most accurate) and zero (least accurate) individually for each firm.

$$AE\_\mathrm{Rank}_{i,j,t} = 100 - \left[\frac{\mathrm{Rank} - 1}{\#\mathrm{Analysts}_{j,t} - 1}\right] \times 100. \tag{3}$$

One shortcoming of all three measures is that analyst accuracy is typically only measured at a single point in the year (e.g., 1 or 6 months prior to the announcement date). In reality, however, analysts make forecasts throughout the year, and continually revise these forecasts as new information appears. As such, it is possible that an analyst may be very inaccurate throughout the year, but have one lucky forecast close to the measurement date and appear to be the most accurate analyst. A more reliable way to measure relative accuracy is to examine accuracy at multiple dates throughout the year, and construct an average accuracy measure over the year.[9]

On each day of the 12 months prior to the day of the earnings announcement, I take the most recent forecast for each analyst and calculate the daily absolute forecast error relative to the future announced earnings. The forecast errors across analysts are compared, and each analyst is ranked daily based on their relative forecast errors.[10] The average daily percentile rank is calculated for each analyst over the full year:

$$\text{Av\_Accuracy\_Rank} = \frac{1}{n}\sum \text{Acc\_Rank}_t. \tag{4}$$

Finally, each analyst receives a summary percentile accuracy rank based on this average. Since brokerage commission is a flow variable, measured over the full year, this flow-based measure of accuracy better captures the consistency of an analyst's relative accuracy throughout the year.

D.2. Measuring Analyst Optimism

Optimism is calculated using FY1 and FY2 earnings estimates. These measures simply remove the absolute value signs from the previous formulas and then follow exactly the same methodology.

$$\text{Opt}_{i,j,t} = (F_{i,j,t} - A_{j,t})/P_{j,t-k}. \tag{5}$$

I also calculate the relative optimism of analyst recommendations (buy, hold, or sell)[11] in the same way. As a robustness check, I also use a measure of optimism that measures the percentage of time that the analyst is above consensus.

D.3. Measuring Forecast Age

Since analysts issue earnings estimates at different points in time, it is important to correct for forecast recency (Brown (1991)). I calculate a relative forecast age measure that ranks analysts daily based on the age of their most recent outstanding estimates. Analysts with the oldest estimates receive a percentile ranking of 1, while those with the most recent a rank of 0. Again I take

[9] Using information from all forecasts on a high frequency (daily) allows us to match flow-based measures of trading volume to a flow-based accuracy measure. Since accuracy is an average deviation over time, this approach is quite analogous to the calculation of integrated volatility measures as described by Andersen et al. (2003).

[10] To eliminate the impact of stale estimates, I delete forecasts if the age of the forecast exceeds 150 days.

[11] Although I/B/E/S provides recommendations on a 1–5 scale, I find that this is inconsistently applied across brokers, with some brokers having all recommendations cluster on values of 1, 3, and 5, while other brokers use all 5 numbers. As such, I reclassify recommendations 4–5 to buy, 3 to hold, and 1–2 to sell. Using the raw recommendations does not significantly change the empirical results.

the average of this measure over the year and rank analysts based on this summary measure.

E. Institutional Considerations

Finally, before proceeding to the empirical analysis, I briefly discuss two institutional considerations relevant to the study. First, sell-side analysts are employed by brokerage firms that provide analyst research to their clients. Clients do not pay directly for the research product, but pay indirectly via brokerage commissions. When clients receive a research report that induces them to trade, they are not obliged to deal through the broker that provided that research. Many institutional investors construct a panel of brokers at the start of a given period in deciding how brokerage will be allocated over the subsequent period in return for access to analyst research. This arrangement may make it difficult to empirically associate brokerage firm volume with analyst actions for a given stock. Nonetheless, Section III demonstrates that despite this effect, strong relationships do exist in the data. Informal discussions with several fund managers in the Australian market reveal that they often *do* trade with the broker whose analyst has provided them with an influential recent report on a stock, in order to maintain a good relationship with that analyst.

Another important consideration is that corporate finance incentives may be significantly larger than trade-generation incentives over the period considered. For example, Hayward and Boeker (1998) report that corporate finance revenues account for four times the equity commission revenues in a typical bank at that time. To control this effect, I include corporate finance controls in my analysis. In the future, if corporate finance and equity trading departments are split, then trade-generation incentives are likely to significantly increase in importance.

III. Empirical Analysis of Analyst Incentives

In this section, I empirically examine the relationship between reputation, optimism, and broker market share. Specifically I examine three empirical hypotheses. First, do higher reputation analysts generate higher broker market share? Second, does better forecasting performance lead to improved analyst reputation? Third, do optimistic analysts generate higher trading volume for their brokerage firms?

The first two hypotheses follow naturally from the neoclassical view, in which investors optimally update their beliefs about analyst ability based on past results, and also pay more attention to analysts with better reputations. The third hypothesis follows from the Spitzer view, whereby investors are fooled by optimistic analysts and trade in response to biased positive forecasts. I now proceed to empirically examine these three hypotheses in turn.[12]

[12] The model subsequently developed in Section IV derives these three hypotheses explicitly.

A. Analyst Reputation and Future Broker Market Share

First, I examine the relationship between an analyst's reputation (the independent variable) and the *future* market share of the brokerage firm that employs this analyst (the dependent variable). The link between reputation and future market share is important to establish, as it provides empirical evidence that reputation is a relevant objective for the analyst. Without this linkage there is little possibility that reputation could act as a disciplining mechanism against opportunistic behavior by the analyst.

Analyst reputation is measured in two ways. The first set of regressions assign a percentage ranking to the analyst based on her survey ranking, with the top analyst receiving a ranking of 1 and the lowest a ranking of 0. The second set of regressions uses a dummy variable for reputation that equals 1 if the analyst is a top three ranked analyst, and 0 if the ranking is outside the top three. In both cases, reputation is measured in year $t - 1$. The relationship is analyzed for each analyst–stock–year unit in the sample, subject to the conditions that the stock exists in the index for the full year, the analyst covers the stock over the year, and a survey ranking exists for the analyst.[13]

To isolate the effects of reputation, two groups of control variables are also included. The first control variable is the size of the broker, since larger brokerage firms are likely to have higher market share due to higher resource levels (e.g., sales staff, research budgets, and distribution infrastructure). Market-wide broker market share across all stocks in a given year is used as a proxy for broker size.[14]

The second group of control variables captures investment-banking relationships between the broker and the stock. Ellis, Michaely, and O'Hara (2000, 2002) show that broker market share is influenced by investment-banking relationships for 3 months after IPOs and SEOs. To control for these effects, I include six dummy variables. The first and second dummies capture whether the broker has acted as either the lead or comanager in an SEO for the stock in the current year. The third and fourth dummy variables measure lead and comanager status over the last 3 years. The fifth and sixth dummy variables measure lead and comanager status for IPOs in the last 3 years.

Table IV presents the results of the pooled regressions with future broker market share as the dependent variable. I calculate t-statistics first using White (1980) robust standard errors to control for heteroskedasticity, and second using the Williams (2000) robust variance estimate to adjust for within-cluster correlation in residuals induced by the same analyst covering several stocks in a given year. Appendix D discusses the calculation of the cluster-adjusted standard errors.

[13] Where I/B/E/S data are available for an analyst, but rating information is missing, I drop the analyst from the analysis. Including these analysts and giving them a zero rating slightly strengthens my conclusions.

[14] Previous research uses the number of analysts employed by the brokerage firm as a proxy for broker size (e.g., Irvine (2001), Hong and Kubik (2003)). Using this proxy does not affect the reputation result, but results in a somewhat less effective broker size control.

Table IV
The Effect of Reputation on Future Broker Market Share

This table analyzes the impact of analyst survey ranking in year t–1 on broker market share in year t. *Analyst ranking* is a percentile ranking of the analyst relative to other analysts covering the stock (1 = highest ranked, 0 = lowest ranked). *Top three analyst* is a dummy variable equaling 1 if the analyst is ranked in the top three for that stock. *Broker size* is the total market share of the broker in year t across all stocks. *SEO lead* is a dummy variable indicating whether the broker has acted as lead manager in that stock in the current year, or in the previous 3 years, respectively. *SEO co* is a dummy variable that corresponds to the manager acting as a comanager. *IPO lead* and *IPO Co* are defined in the same way. Analyst–stock–years are used as the unit of analysis, with both robust and cluster-adjusted t-statistics presented. The dependent variable is the market share of the broker in that stock for that year. Only stocks where the broker has an analyst covering the stock are included (and where a ranking for the analyst exists). Results are presented for all stocks and for large (Top 100) stocks separately.

	Broker Market Share (t)											
	All Stocks						Large Stocks (Top-100)					
	Coefficient	White t-Statistics	Cluster t-Statistics	Coefficient	White t-Statistics	Cluster t-Statistics	Coefficient	White t-Statistics	Cluster t-Statistics	Coefficient	White t-Statistics	Cluster t-Statistics
Constant	0.007	3.75	2.69	0.016	9.26	6.15	−0.005	−2.32	−1.76	0.005	2.85	2.17
Analyst ranking (t−1)	0.020	7.78	5.43				0.028	10.23	8.17			
Top three analyst (t-1)				0.015	9.23	5.81				0.018	9.93	8.03
Broker size (t)	0.690	29.83	20.23	0.700	31.13	21.37	0.813	31.60	24.33	0.839	33.45	26.10
SEO1 lead	0.037	3.44	3.52	0.037	3.45	3.53	0.042	3.32	3.37	0.042	3.31	3.37
SEO1 co	−0.003	−0.22	−0.22	−0.004	−0.30	−0.30	−0.005	−0.41	−0.41	−0.005	−0.42	−0.42
SEO3 lead	0.063	9.25	9.14	0.063	9.22	9.13	0.044	6.16	5.91	0.044	6.20	5.97
SEO3 co	0.014	1.34	1.34	0.015	1.42	1.42	0.010	0.97	0.97	0.011	1.07	1.06
IPO3 lead	0.087	6.66	6.68	0.087	6.66	6.68	0.036	2.90	2.91	0.035	2.88	2.89
IPO3 co	−0.009	−1.78	−1.75	−0.010	−1.77	−1.75	−0.007	−1.38	−1.36	−0.006	−1.23	−1.22
Observations	10,717			10,717			5,858			5,858		
Adjusted R^2	18.74%			18.91%			27.33%			27.53%		

We can see from Table IV that analyst reputation in the previous year has a highly significant positive impact on broker market share in the following year with a t-statistic of 7.8 using White adjustments, and 5.4 using clustering. This confirms the first hypothesis that future trading volume is increasing in the reputation of the analyst. The significance of the reputation variable is higher for larger (top 100) stocks. This relationship between analyst reputation and future own-broker volume has, to my knowledge, not been previously established in the literature.

Table IV also reveals that larger brokers have higher market shares, as we might expect. Additionally, acting as a lead manager for an IPO or an SEO significantly increases the market share of the broker in that stock over the following 3 years, by 6.3% for SEOs and 8.7% for IPOs. Conversely, acting as a comanager has no significant affect on market share in the following 3 years. This result is consistent with Ellis et al. (2000, 2002) and additionally demonstrates that the relationship persists for an even longer horizon than the 3 months that they document.

In terms of economic significance, Table IV shows that a top three ranked analyst increases broker market share by 1.8% for a top 100 stock. In this market, the typical institutional trading commission rate is around 15bp and a typical analyst covers around 7.1 stocks in her given sector. For a large sector such as banks, the additional 1.8% market share equates to around \$A6.88m extra commission revenue for a top three analyst relative to a non top-three ranked analyst for turnover levels equal to those of the last year of the sample.[15] This revenue is *incremental* to the revenue generated by simply covering a given stock. Coverage alone generates an additional market share of 2.4% in my data sample.[16] The effect of reputation on future trading commissions appears economically large.

To ensure that the reputation–market share relationship is robust, I run the following checks. First, running the regression separately for each year from 1995 to 2002 yields a positive coefficient on the survey-ranking variable in every single year. The Fama–Macbeth coefficient for annual cross sections on this variable is 0.027, with a standard error of 0.004 (t-statistic of 6.12), which is highly significant. Second, I redo the analysis using reputation in year t, rather than reputation in year $t-1$ as the independent variable of interest. This increases the number of observations by around 13% (due to the inclusion of an extra year), and yields coefficients slightly higher and more significant than using reputation measured at year $t-1$. Third, I transform the market share variable using a log specification as in Khorana and Servaes (2002). This significantly improves the normality of the residuals, and increases the fit of the regression (e.g., R^2 increases from 18 to 28% in the first regression). The

[15] To calculate this result, I take total dollar trading volume (two-sided) over the last year of the sample in index bank stocks (\$255bn), then multiply by 1.8% and by a commission rate of 15bp to get \$6.88m. The equivalent result for some other sectors is media (\$2.79m), health care (\$0.94m), telcos (\$1.98m), materials (\$5.98m), and listed property trusts (\$1.61m).

[16] Irvine (2001) shows using Canadian data for 1994 that coverage alone generates 3.8% of incremental market share.

transformation also significantly increases the t-statistics on the reputation variable; however, the economic interpretation of the coefficient is less transparent. Fourth, I calculate t-statistics using broker–year clusters rather than analyst–year clusters to allow for common firm-wide shocks to market shares. I also adjust for firm–year clusters to account for any negative autocorrelation due to the adding-up constraint of broker market shares. I then exclude negative earnings stocks to check that write-offs do not affect the result. Finally, I redo the analysis using only the largest nine brokers in the sample. The reputation coefficient remains strongly significant for all of these last four variations.[17]

B. Analyst Performance and Reputation

This section tests whether analyst reputation is increasing in the accuracy of recent forecasts. Demonstrating this link provides evidence that investors update their beliefs about analyst ability in a rational manner based on recent performance. It also provides an incentive for analysts to care about their accuracy, given that we have just shown that reputations are economically valuable.

Of course, in reality, an analyst's reputation is influenced by factors other than accuracy. For example, timeliness of forecasts is likely to be highly important to investors. Some analysts may trade off accuracy against timeliness in order to communicate private information rapidly to investors.[18] Other less quantifiable factors, such as an analyst's responsiveness to client requests or knowledge of the industry as conveyed in written reports, are also likely to influence reputation in a significant way.

Several control variables are included to capture these factors. The average age of the analyst's forecasts relative to other analysts covering the stock is used to capture timeliness. The relative optimism of the analyst's forecasts is included, as are investment-banking relationships where the firm acts as the lead broker in either an SEO or IPO in the past 3 years.[19] Finally, the size of the broker is also included as a control.

The independent variable of most interest for our test is the relative accuracy of the analyst. The dependent variable in the regressions is analyst reputation, measured by the percentile rank of the analyst in the current end-of-year survey. Table V presents the results of the regression with analyst reputation as the dependent variable. Both univariate and multivariate regressions are presented, using robust cluster-adjusted t-statistics that control for correlated analyst–year effects. We can see from the univariate results that the analyst's reputation is significantly positively related to relative accuracy in that year. Including the control variables does not affect this conclusion. Thus, the data support the second hypothesis, that accurate analysts receive higher survey

[17] In unreported results, I also verify that changes in reputation lead to higher future market share. Also including the lagged dependent variable as a control does not affect the result.

[18] Cooper, Day, and Lewis (2001) find that timeliness can be used to identify high ability lead analysts, whose forecasts have a greater impact on stock prices.

[19] Investment banking relationships in which the broker acts as a co-manager have no effect on the regression and are excluded for brevity.

Table V

The Effect of Accuracy on Analyst Reputation

This table analyzes the impact of relative analyst accuracy during year t on end-of-year analyst reputation. *FY1 accuracy* is a percentile ranking of the analyst's accuracy relative to other analysts covering the stock (1 = most accurate, 0 = least accurate) averaged over the full year. *FY1 estimate age* is a percentile ranking of the average age of the analyst's estimates relative to other analysts covering the stock (1 = least timely, 0 = most timely). *FY1 optimism* is a percentile ranking of the analyst's relative optimism about FY1 earnings averaged over the year (1 = most optimistic, 0 = least optimistic). *Broker size* is the total market share of the broker in year t across all stocks. *SEO lead* is a dummy variable indicating whether the broker has acted as lead manager in that stock in the current year, or in the previous 3 years, respectively. *IPO lead* is defined in the same way. Analyst–stock–years are used as the unit of analysis, with both robust and cluster-adjusted t-statistics presented. The dependent variable is the percentile ranking of the analyst at the end of year t.

	Analyst Reputation (t)					
	All Stocks			Large Stocks (Top 100)		
	Coefficient	White t-Statistics	Cluster t-Statistics	Coefficient	White t-Statistics	Cluster t-Statistics
Constant	0.611	52.09	32.58	0.568	40.02	26.83
FY1 accuracy	**0.021**	**2.36**	**2.28**	**0.025**	**2.22**	**2.15**
FY1 estimate age	−0.052	−5.81	−4.47	−0.080	−7.08	−5.44
FY1 optimism	−0.014	−1.53	−1.36	−0.017	−1.49	−1.32
Broker size (t)	0.819	8.27	4.33	1.299	10.92	6.12
SEO1 lead	0.023	0.95	0.93	0.014	0.43	0.43
SEO3 lead	0.033	1.93	1.90	0.061	2.64	2.65
IPO3 lead	0.021	0.87	0.88	0.065	2.12	2.12
Observations	9,208			5,748		
Adjusted R^2	1.66%			4.19%		

ratings than nonaccurate analysts, consistent with the market adjusting its beliefs about the analyst's ability in a rational manner.

The control variables reveal some interesting results. First, reputation is strongly increasing in the size of the broker. This result is consistent with larger brokers employing better analysts and having more resources at their disposal. Second, reputation is significantly decreasing with the average age of the analyst's estimates. The coefficient on timeliness is 2.5 times the size of the coefficient on accuracy, suggesting that this variable may be significantly more important than accuracy in determining an analyst's ranking. Finally, the coefficients on investment-banking and optimism variables are insignificant.

To ensure that the accuracy–reputation linkage is robust, I perform the following checks. First, the analysis is repeated for large (top 100) stocks only. This increases the size of the accuracy coefficient in the multivariate regression by 19%. Second, t-statistics are recalculated using broker–year clusters to account for common shocks to the reputation of analysts from the same brokerage firm. The accuracy variable remains significant. Third, the analysis is repeated using the top nine brokers only. Fourth, I exclude negative earnings stocks to ensure that write-offs are not influencing the result. Fifth, I de-bias raw earnings forecasts by both an analyst-specific and an overall average level of optimism before ranking analysts on the basis of accuracy, and repeat the regression analysis.[20] Finally, I calculate t-statistics using stock–year clusters to allow for negative cross-correlations in rankings for the same stock. The empirical finding is robust to all of these variations.

C. Analyst Optimism and Broker Market Share

This section tests whether optimistic analysts generate higher trading volume. Establishing the link between optimism and market share establishes that analysts have an incentive to be optimistic on average, even in the absence of investment-banking affiliations or management access concerns.

To proxy for optimism, I use three separate measures. The first is the relative optimism of the analyst's FY1 earnings forecast relative to other analysts covering the same stock. This is measured as a percentile rank, with 1 being the most optimistic analyst on average throughout the year, and 0 being the least optimistic analyst. The second proxy is the relative optimism of the analyst's FY2 earnings forecast. I include these two measures separately, since it is plausible that analysts may communicate optimism via longer-term forecasts, since these are harder for the investor to verify and the analyst may be able to get away with excessive optimism more easily in distant forecasts. The final measure of optimism is the actual recommendation issued by the analyst (e.g., buy, hold, or sell). Recommendation optimism is likely to be the least costly to a broker's reputation, since recommendations typically are not accompanied by a specific time horizon. Unfortunately, recommendation information is only available on I/B/E/S for a subset of firms in my sample. This significantly reduces the sample size from around 14,000 to 3,000 analyst–stock–years.

The dependent variable is the broker market share in the current year. I include investment-banking affiliations, broker size, and reputation as controls. The results of the analysis are presented in Table VI. The first four regressions omit the analyst reputation variable (increasing the size of the sample by around 75% for the FY optimism regressions), while the second four include reputation. Standard errors are corrected for analyst–year clustering.

The results show that individually, FY1, FY2, and recommendation optimism each positively influence broker market share in the current year, consistent

[20] If some analysts are consistently biased in one direction, the market may implicitly adjust their beliefs about the analysts' true forecasts before determining the accuracy of the forecasts. For example, the market may deduct 5% from a particular analyst's forecast and treat this as the "true" forecast of the analyst. To adjust for this possibility, I use two methods. First I calculate an analyst-specific bias using all previous data available for that analyst. At each point in the sample, I deduct the historical bias for that particular analyst from her current forecast. Second, I calculate an average optimism deflation function using the average level of optimism of all analysts at each day prior to the actual earnings date based on historical data. I find that my results in Table V are robust to both these adjustments; namely survey ranking is significantly positively related to accuracy. I thank the referee for this helpful suggestion.

Table VI
The Effect of Optimism on Broker Market Share

This table analyzes the impact of relative optimism in year t on broker market share in year t. *FY1 optimism* is a percentile ranking of the analyst's FY1 EPS forecast relative to other analysts covering the stock (1 = most optimistic, 0 = least optimistic) averaged over the year. *FY2 optimism* and *Rec optimism* are constructed similarly using FY2 EPS forecasts and recommendations (buy, hold, sell), respectively. *Analyst ranking* is a percentile ranking of the analyst's accuracy relative to other analysts covering the stock (1 = highest ranked, 0 = lowest ranked). *Broker size* is the total market share of the broker in year t across all stocks. *SEO Lead* is a dummy variable indicating whether the broker has acted as lead manager in that stock in the current year, or in the previous 3 years, respectively. *IPO Lead* is defined in the same way. Analyst–stock–years are used as the unit of analysis and cluster-adjusted t-statistics are presented. The dependent variable is the market share of the broker in that stock for that year. Only stocks where the broker has an analyst covering the stock are included (and where optimism and ranking information for that analyst exists, which significantly decreases the sample size for regressions using the recommendation data). Results are calculated using all stocks in the sample.

	Dependent Variable = Broker Market Share (t)															
	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Coefficient	Cluster t-Statistics	Coefficient	Cluster t-Statistics	Coefficient	Cluster t-Statistics	Coefficient	Cluster t-Statistics	Coefficient	Cluster t-Statistics	Coefficient	Cluster t-Statistics	Coefficient	Cluster t-Statistics	Coefficient	Cluster t-Statistics
Constant	0.002	5.99	0.006	3.42	−0.033	−6.47	−0.034	−6.53	0.007	1.99	0.001	0.18	−0.038	−5.11	0.038	−5.20
FY1 optimism (t)	**0.002**	**3.52**					**−0.005**	**−1.42**	**0.005**	**2.08**					**−0.003**	**−0.69**
FY2 optimism (t)			**0.015**	**7.82**			**0.010**	**2.65**			**0.017**	**6.58**			**0.007**	**1.73**
Rec optimism (t)					**0.016**	**8.98**	**0.015**	**8.43**					**0.016**	**7.82**	**0.016**	**7.43**
FY1 estimate age (t)	−0.010	−5.62	−0.009	−5.20	−0.006	−1.63	−0.005	−1.48	−0.006	−2.61	−0.006	−2.34	−0.003	−0.89	−0.002	−0.62
Analyst ranking ($t-1$)									0.022	5.59	0.022	5.48	0.012	2.51	0.012	2.46
Broker size (t)	0.845	49.32	0.850	48.00	0.913	14.29	0.912	25.02	0.706	18.38	0.712	18.33	0.856	14.24	0.853	13.87
SEO1 lead	0.036	3.86	0.035	3.78	0.054	2.98	0.055	2.92	0.041	3.58	0.040	3.52	0.055	2.73	0.056	2.74
SEO3 lead	0.057	10.51	0.057	10.37	0.028	2.83	0.028	2.78	0.057	8.17	0.056	8.10	0.029	2.65	0.028	2.60
IPO3 lead	0.087	7.54	0.086	7.43	0.033	1.94	0.032	2.02	0.082	5.64	0.082	5.52	0.034	1.72	0.033	1.70
Observations	14,216		13,832		3,375		3,305		8,286		8,103		2,569		2,569	
Adjusted R^2	29.2%		29.1%		35.0%		35.0%		18.9%		19.3%		24.8%		24.8%	

with the hypothesis. When all three variables are included in the regression, the recommendation optimism variable dominates the other two variables, consistent with the interpretation that analysts are more likely to transmit optimism via softer messages rather than by near-term earnings forecasts. However, it should be noted that this final result is based on a relatively small data sample, so it is still likely that EPS optimism is an important channel on its own.

As we saw in Section III.A, investment-banking affiliations are an important control variable, and significantly influence the level of broker market share in a given stock. Broker size and analyst reputation both enter significantly, consistent with our previous results.

To ensure that the optimism results are robust, I perform the following checks. First, I recalculate the standard errors using both broker-level and firm–year level clustering rather than analyst-level clustering. This does not alter the economic findings; FY1, FY2, and recommendations each remain individually significant in regressions (1) to (3) and (5) to (7), and similar results apply for regressions (4) and (8) with recommendations dominating the other variables. Second, I repeat the regressions for each separate year from 1995 to 2002. The coefficients on FY2 and recommendation optimism in the univariate regressions are statistically significantly positive in every year, while the coefficient on FY1 optimism is positive in every year though significant in only two of the years. Third, I redo regressions (1) to (8) only for the top nine brokers. The results are unchanged. Fourth, I log-transform the dependent variable as in Section III.A. This improves the fit of the regressions and strengthens the FY2 and recommendation optimism results, while the FY1 optimism result becomes weaker. Next, I exclude all stocks that have had an IPO or SEO in the last 3 years. The optimism findings remain highly significant. Finally, I exclude stock–years with negative earnings, which does not change the results. In summary, the FY2 and recommendation optimism results appear quite robust, while the FY1 optimism result is somewhat less so. Overall however, the results are strongly supportive of the third hypothesis—that more optimistic analysts generate higher trading volume for their firms.

As a final robustness check on the regression results for Tables IV–VI, I examine the data for evidence of multicollinearity. Variance inflation factors are calculated for each independent variable in each of the regressions, and the results are presented in Table VII along with condition numbers for the regressions. The results show that variance inflation factors do not exceed two, and the condition numbers are low, indicating that multicollinearity is not affecting the results of the analysis. Examining pair-wise correlations between the independent variables confirms this result.

To conclude, the first two empirical results support the neoclassical view that investors act rationally. Namely, high reputation analysts generate higher future trading volume and better forecasting performance leads to a higher reputation. However, the third result, that optimistic forecasts generate higher current trading volume, appears to support the Spitzer view. In the next section, I reconcile these apparently contradictory findings using a model with fully rational agents and asymmetric information.

Table VII

Variance Inflation Factors

This table calculates variance inflation factors for each of the independent variables in the three regressions (Table IV to Table VI). Variance inflation factors are calculated as $1/(1 - R^2)$, where R^2 is the R-squared in a regression of each independent variable on the remaining independent variables. Condition numbers are also presented for each regression. Independent variables are defined in the captions of each of the appropriate tables and in Section II of the paper.

	Variance Inflation Factors		
Variable	Table IV	Table V	Table VI
Total market share	1.010	1.014	1.019
Survey_m1	1.012		1.010
Accuracy FY1		1.033	
Relative age FY1		1.016	1.017
Relative optimism FY1		1.032	1.501
Relative optimism FY2			1.523
Relative optimism Rec			1.044
SEO1 lead	1.775	1.753	1.629
SEO1 co	1.260		
SEO3 lead	1.801	1.775	1.639
SEO3 co	1.261		
IPO3 lead	1.020	1.022	1.011
IPO3 co	1.001		
Condition number	8.50	2.81	3.07

IV. Model of Reputation and Trade Generation

In this section, I develop a simple model describing the strategic interaction between an investor and an analyst. The interaction is modeled as a dynamic game of incomplete information. The primary objective of the model is to reconcile the three empirical results found in Section III within a simple fully rational agent framework. In addition, the model also produces three further testable hypotheses that I subsequently empirically test in Section V.

A. Description of Economy

There are two possible future states of the world (labeled high and low) that are equally likely. A single stock, with initial price P_0, is available with payoffs x_{high} and x_{low} in these two states[21] where $x_L < P_0 < x_H$.

There exists a one-period investor with log utility and initial wealth W. His initial beliefs about the state of the world are given by $\lambda = \Pr(x_{\text{high}}) = 0.5$, and he is endowed with δ_0 shares in the single stock where:

$$\delta_0 = \frac{-W(\lambda(x_H - P_0) + (1 - \lambda)(x_L - P_0))}{(x_H - P_0)(x_L - P_0)}. \tag{6}$$

[21] The use of binary states makes the modeling significantly more tractible and has been used extensively in past reputation modeling, for example, Morris (2001) and Sharfstein and Stein (1990).

This seemingly complicated expression is just equal to his optimal shareholding, given his initial beliefs (see Appendix A for details).

The investor employs a sell-side analyst at the start of the period to forecast the future state. I assume that he only employs a single analyst, and is obligated to trade through the brokerage firm employing this analyst if he revises his beliefs on the basis of the analyst's advice.[22] The sell-side analyst may be one of two types; a "smart" analyst (who receives informative private signals) or a "dumb" analyst (whose private signals are just noise). Neither the investor nor the analyst initially knows the analyst's actual type,[23] but they hold a common prior that $P(\text{smart}) = \theta$ where $0 \leq \theta \leq 1$.

At the start of the period, the sell-side analyst receives a noncontractible binary private signal[24] ($s = s_{\text{high}}$ or $s = s_{\text{low}}$) about the future state with the following properties:

$$P(s_{\text{high}} \mid x_{\text{high}}, \text{smart}) = p \tag{7a}$$

$$P(s_{\text{high}} \mid x_{\text{low}}, \text{smart}) = 1 - p \tag{7b}$$

$$P(s_{\text{high}} \mid x_{\text{high}}, \text{dumb}) = P(s_{\text{high}} \mid x_{\text{low}}, \text{dumb}) = 0.5 \tag{7c}$$

with $0.5 < p < 1$.

After receiving the private signal, the analyst chooses a binary message ($m = m_{\text{high}}$ or $m = m_{\text{low}}$) that she[25] then sends to the investor. This message need not be truthful, that is, she may choose to send m_{high} to the investor even after observing s_{low}. The investor receives the message and optimally updates his beliefs about the expected payoff from the stock. His posterior belief is given by $\lambda^* = P(x_{\text{high}} \mid m)$, which will be determined in the equilibrium of the model (Sec. IV.B).

Given these revised beliefs, the investor recalculates his optimal holding of the stock and trades to achieve this holding. For simplicity I assume that the investor is sufficiently small that his actions do not influence the stock price, which remains constant at P_0.[26] The optimal holding given the revised beliefs is given as:

[22] The single analyst assumption allows us to abstract for the moment from well-documented issues including analyst herding and exaggeration. For an examination of these issues see Scharfstein and Stein (1990), Trueman (1994), and Zitzewitz (2001). For a discussion of the "obligation to trade" assumption see Section II.E.

[23] This assumption is quite important for the equilibrium of the model.

[24] The signal is not verifiable, that is, a court cannot distinguish whether the analyst received the high or low signal. This prevents a contract from being written with payment contingent on the analyst truthfully reporting the private signal.

[25] For clarity of exposition I refer to the analyst as "she" and to the investor as "he" throughout the paper.

[26] Relaxing this assumption to allow the analyst's signal to be *partially* incorporated in the share price would not alter the economic conclusion of this model, but decreases the tractability of the calculations. If the signal is *fully* incorporated in the price, the results do not go through. This assumption also enables us to avoid considerations of how the investor would strategically modify his demand to exploit monopolistic private information as in a typical Kyle (1985) model setup.

$$\delta_1 = \frac{-W\left(\lambda^*(x_{\mathrm{H}} - P_0) + (1-\lambda^*)(x_{\mathrm{L}} - P_0)\right)}{(x_{\mathrm{H}} - P_0)(x_{\mathrm{L}} - P_0)}. \tag{8}$$

His desired trade, $\delta_1 - \delta_0$, is directly proportional to his revision in beliefs and is given as:

$$\text{Desired Trade} = \delta_1 - \delta_0 = \alpha(\lambda^* - \lambda) \tag{9a}$$

where

$$\alpha = \frac{-W(x_{\mathrm{H}} - x_{\mathrm{L}})}{(x_{\mathrm{H}} - P_0)(x_{\mathrm{L}} - P_0)} > 0. \tag{9b}$$

To make the model interesting[27] (and realistic), assume that the investor faces binding short-sales constraints with probability q. This implies that the investor may not always be able to implement his desired trade after receiving a low message that induces a downward revision in beliefs. In reality, short-sales constraints are frequently generated by institutional restrictions on short selling. For example, Almazan et al. (2005, p. 11) find that around two thirds of mutual fund managers are specifically restricted from short selling in their mandates, and of the one third that are allowed, only 10% of them actually *did* short any stocks in 2000 (59 funds out of 1,838 sampled). Another reason for limited shorting may be high lending fees or the inability to short some stocks (Lamont (2003)).

If short-sales constraints are binding, the investor does not undertake any trade. Otherwise, he is able to implement his full desired trade. The *expected* trade generated given a positive and negative revision in beliefs is given respectively by:

$$E(\text{Trade} \mid \text{Positive revision}) = \alpha(\lambda^* - \lambda) \tag{10a}$$

$$E(\text{Trade} \mid \text{Negative revision}) = (1-q)\alpha(\lambda^* - \lambda). \tag{10b}$$

Thus, if $q > 0$, a negative revision to beliefs generates a *lower* absolute expected trade size than an equivalently sized positive revision to beliefs. This asymmetry is crucial to the results of the model as it provides an incentive for the analyst to be optimistic.

Finally in our model, at the end of the period, the true state of the world (x_{high} or x_{low}) is revealed to both the investor and the analyst.[28] The investor compares

[27] Without such an asymmetry in the model, the analyst always chooses to report a truthful message, since the expected posterior reputation is higher than if she sends a dishonest message. There are various ways of introducing asymmetry in the analyst's incentives. For example, previous researchers have examined investment banking affiliations and management access as possible incentives for the analyst to lie optimistically in given situations. In this paper I focus on a third channel, the trade generation incentive facing analysts, and introduce the asymmetry via selling constraints.

[28] Consistent with most previous research on cheap talk, for example, Crawford and Sobel (1982) and Benabou and Laroque (1992), I use a single round of communication. Relaxing this assumption would be an interesting area for future research.

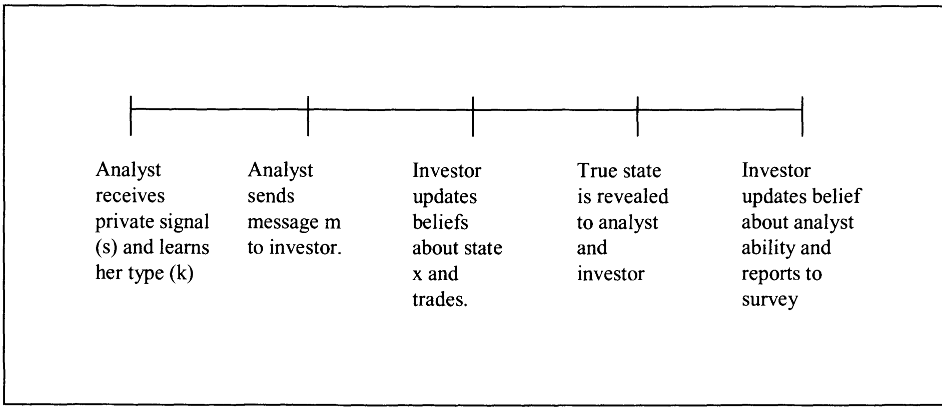

Figure 1. Timeline of events in the model.

the message sent by the analyst, m, to the realized state, x, and optimally updates his beliefs about the analyst's ability. The updated posterior belief is given by $\theta^* = P(\text{smart} \mid m, x)$. The investor truthfully reports this updated belief to a survey, then dies. I will refer to this posterior belief as the "reputation" of the analyst. Figure 1 presents a timeline of events in the model.

The analyst is employed by a brokerage firm that compensates her based both on the level of trading commission she generates in a given period and on her survey ranking at the end of the period. The survey ranking is valuable to the brokerage firm, since it leads to higher future trading volume in subsequent periods, given that subsequent investors use the ranking as their prior, and that higher reputation analysts generate larger revisions in beliefs (which I prove is true in equilibrium in Sec. IV.B). Let the percentage trading commission rate be given as c.

The analyst's objective function may be specified in reduced form as:

$$\max_{m} c.E(\text{Trade} \mid m) + k.E(\theta^{\text{posterior}} \mid m). \tag{11}$$

That is, the analyst cares both about how much commission she generates during this period, and about her reputation for being smart at the end of the period.[29] The parameter $k \in [0, \infty)$ represents how much the analyst cares about her future reputation and is known by the analyst but not by the investor.

[29] A different way to model this game would be within a repeated game framework, where the analyst's utility function is given as the discounted value of all future trading commissions generated. In this game "reputation effects" would arise endogenously, given certain parameter restrictions. However, this approach also greatly complicates the model without adding significantly to the basic point I am trying to make. For examples of this approach see the papers by Diamond (1989) and Benabou and Laroque (1992). In unreported results, available on request, I am able to map a simplified version of my model onto Theorem 1 of Benabou and Laroque (1992), verifying that my main equilibrium results do not disappear in a richer multiperiod model. Namely, consensus optimism survives and remains partly credible for an unbounded period of time in an infinitely repeated game.

The investor therefore faces incomplete information about the analyst's payoff function, but he does know the probability distribution of k given by the cdf $F(k)$. At the start of the single period game, nature chooses the analyst's k-type according to this probability density function. The investor's uncertainty about k is the primary driving force behind the model's results.[30]

The parameter k may be interpreted in at least two ways.[31] First, k may represent stochastic outside options facing the analyst in that period. A low value of k indicates attractive outside options, so the analyst cares less about her reputation. A high value indicates that the analyst values her reputation highly. To prevent the investor from learning about k, I assume that the outside options facing the analyst are randomly changing over time (e.g., attractive portfolio management positions arrive randomly at the start of each period).

A second interpretation is that k is persistent across periods for a given analyst. This may reflect the analyst's career concerns; for example, a young analyst may have a high k and value her reputation highly (Holmstrom (1982)), while an analyst in her final year may have a low k due to the final period effects of the game. In this interpretation, investors must be assumed to be unable to communicate information about the analyst's k-type across periods, or alternatively, are unable to tell whether the analyst is near the final round of her game.

We will see in equilibrium that the desire to generate both high current commission and a high end-of-period reputation generates conflict for the analyst only when she receives a low private signal. For a high private signal, s_{high}, her two objectives are aligned, since sending a positive message generates both higher trading volume and a higher expected posterior reputation (since truthful messages are more likely to be correct). Conversely, for the low private signal, s_{low}, sending the truthful low message generates lower trading volume than a high message (due to short-sales constraints) but also generates a higher expected end-of-period expected reputation. Thus, a conflict exists between trade-generation and reputational concerns.

Her ultimate choice is given by the message that maximizes her objective function. If the following condition holds, then she truthfully reports the low message:

$$c[E(\text{Trade} \mid m_{\text{H}}) - E(\text{trade} \mid m_{\text{L}})] \leq k\left[E\left(\theta^{\text{posterior}} \mid m_{\text{L}}\right) - E\left(\theta^{\text{posterior}} \mid m_{\text{H}}\right)\right]. \quad (12)$$

Otherwise she lies and reports m_{H}. If the analyst's type k is large enough that she reports truthfully I will refer to her as a "good" analyst. Otherwise, if she chooses to lie I will refer to her as an "evil" analyst.

The analyst's choice depends on the investor's beliefs in equilibrium, and on her k-type. The investor's beliefs depend in turn on the strategy he expects the

[30] See Morgan and Stocken (2003) for a related model examining how investors' uncertainty about an analyst's type leads to equilibrium overoptimism and a significant loss in information transmission.

[31] Benabou and Laroque (1992, p. 941) use a similar technique, allowing the agent's type to follow a stochastic process. This makes the learning problem more difficult. In equilibrium, information is transmitted and credibility does not vanish.

analyst to follow. These issues are examined in the equilibrium discussion to which I now turn.

B. Specification of Equilibrium

In this section, I derive an equilibrium for this simple game. The solution concept I use is perfect Bayesian equilibrium. This solution concept requires that the strategy profile of each agent is sequentially rational given his/her beliefs, and that beliefs are generated using Bayes' rule. In addition, beliefs off the equilibrium path must be specified. Proposition 1 gives the equilibrium in the investor–analyst game.

PROPOSITION 1: *Suppose the following condition*[32] *holds,*

$$q > 1 - \left(\frac{\pi}{2-\pi}\right), \tag{13}$$

then there exists a perfect Bayesian equilibrium with the following features,

(i) An analyst with type $k \geq k^*$ always reports truthfully, sending the low message m_{low} when she receives the low private signal s_{low}, and sending the high message m_{high} when receiving the high private signal s_{high}. An analyst with type $k < k^*$ always reports the high message, irrespective of her private signal. The critical level of k^* is given implicitly by

$$k^* = \frac{c\alpha\left(\frac{\pi}{2-\pi} + q - 1\right)(0.25 - (p-0.5)^2\theta^2\pi^2)}{\pi(1+\pi)(p-0.5)(1-\theta)\theta}, \tag{14}$$

where $\pi = \Pr(k \geq k^*)$ is the probability that the analyst's type exceeds k^*.

(ii) An investor with beliefs π, θ buys $\delta_2^{\mathrm{H}} - \delta$, shares after receiving a high message from the analyst where,

$$\delta_2^{\mathrm{H}} - \delta_1 = \alpha(p-0.5)\theta\left(\frac{\pi}{2-\pi}\right). \tag{15}$$

If the investor does not *face short-sales constraints, then he sells $-\delta_2^{\mathrm{H}} + \delta_1$ shares after receiving the low message from the analyst where,*

$$-\delta_2^{\mathrm{L}} + \delta_1 = \alpha(p-0.5)\theta. \tag{16}$$

If the investor does *face short-sales constraints then he sells no shares after receiving the low message.*

[32] Since π is determined endogenously in the equilibrium, it is not generally possible to express it as an explicit function of the exogenous parameters. For specific numerical values of the exogenous parameters and a particular distribution of k, it is however possible to solve for the minimum level of q to ensure that this condition holds.

(iii) *After the true state is revealed, the investor reports his updated posterior belief* $\theta^* = \Pr(\text{smart} \mid x, m)$ *to a survey. There are four possible survey responses given as,*

$$P(\text{smart} \mid m_{\rm H} \,\&\, x_{\rm H}) = \frac{(0.5 + (p - 0.5)\pi)\theta}{0.5 + (p - 0.5)\theta\pi} \tag{17a}$$

$$P(\text{smart} \mid m_{\rm H} \,\&\, x_{\rm L}) = \frac{(0.5 - (p - 0.5)\pi)\theta}{0.5 - (p - 0.5)\pi\theta} \tag{17b}$$

$$P(\text{smart} \mid m_{\rm L} \,\&\, x_{\rm H}) = \frac{(1 - p)\theta}{0.5 - (p - 0.5)\theta} \tag{17c}$$

$$P(\text{smart} \mid m_{\rm L} \,\&\, x_{\rm L}) = \frac{p\theta}{0.5 + (p - 0.5)\theta}. \tag{17d}$$

(iv) *This equilibrium has the following characteristics.*
   (a) *The investor's trade size is increasing in his initial belief about the analyst's ability (i.e., higher reputation analysts generate more trade).*
   (b) *Analysts with accurate messages achieve increases in reputation.*
   (c) *High messages generate more trade on average than low messages.*
   (d) *The average message sent in equilibrium is optimistic. If all analysts were honest, the average message sent would be* 0.5. *However, in this equilibrium the average message sent is,*

$$E(m) = 1 - 0.5\pi > 0.5 \tag{18}$$

when $\pi < 1$.

Proof of Proposition 1: See Appendix A.

We can see from Proposition 1 that the three empirical results from Section III arise in the equilibrium. Higher reputation analysts generate higher future trading volume, accurate analysts are rewarded with increases in their reputation, and optimistic analysts generate more trade for their firms.

We can also see that investors act in a rational way in this equilibrium, updating their beliefs via Bayes' rule and having correct prior beliefs about the parameters of the model. Investors face asymmetric information about the analyst's concerns for her future reputation, and adjust their actions and beliefs accordingly. The analyst correctly anticipates how investors will react to her messages and in turn optimizes her strategy.

We can illustrate the implications of the equilibrium via a simple numerical example. If we assume a uniform distribution of k between 0 and 1, with parameters of $c = 0.005$, $\theta = 0.5$, $p = 0.60$, and $q = 0.5$, then the critical level is $k^* = 0.0942$. This implies that the analyst has a 90.58% probability of being a "good" type, and the average message sent in equilibrium is 0.547 (compared to the unbiased true signal of 0.50). Additionally, condition (13) is satisfied, since $q = 0.5 > 0.172 = 1 - \pi/(2 - \pi)$.

We can also generate several comparative statics results from this model as outlined in Proposition 2.

PROPOSITION 2: *Given the equilibrium in Proposition 1, the following comparative statics results hold for the equilibrium level of optimism E(m),*

1. *The expected message is increasing in the level of short-sales constraints, q.*
2. *The expected message is decreasing in the precision of the private signal, p.*

Proof of Proposition 2: See Appendix B.

Proposition 2 predicts that consensus optimism is higher for stocks that have higher probabilities of short-sales constraints. The intuition behind this result is straightforward. As the level of short-sales constraints becomes higher, the difference in trading volume between a high and low message becomes larger, so the incentive for the analyst to lie optimistically becomes stronger. Thus, the critical level of k increases and the probability that the analyst reports truthfully drops. As long as condition (13) holds, optimistic messages still generate more trade.

Proposition 2 also predicts that when the informativeness of the private signal decreases, the equilibrium level of optimism rises. In this case, the analyst is less likely to be "caught out" by sending an incorrect signal, and therefore the expected loss in reputation from reporting an incorrect message is lower.

Again, using our simple numerical example with k uniform between 0 and 1, and parameters of $c = 0.05$, $\theta = 0.5$, Figure 2 plots the average message sent in equilibrium for different values of p and q. We can see from Figure 2 that the average message sent is always biased optimistically, and that this optimism becomes larger as short-sales constraints, q, increase and as signal informativeness, p, decreases.

So far, we have maintained the assumption that investors act in a fully rational manner and have not needed to appeal to any behavioral stories to generate any of the results. However, it is interesting to compare the predictions of this model to a behavioral explanation of the phenomena.

To do this (and subsequently to test the Spitzer view against the neoclassical view), we can adjust our model to impose a specific behavioral error on investors' beliefs. One argument commonly used by regulators (and behavioralists) is that investors (particularly small investors) often naively believe that analysts always report truthfully, allowing them to be consistently fooled by optimistic messages. For example, the *Wall Street Journal* (2002) reported that

> Investigators had spent months looking into allegations that analysts had hyped the stocks of companies that generated fat investment-banking fees for their firms, misleading small investors when the companies—including money-losing Internet start-ups—went bust.

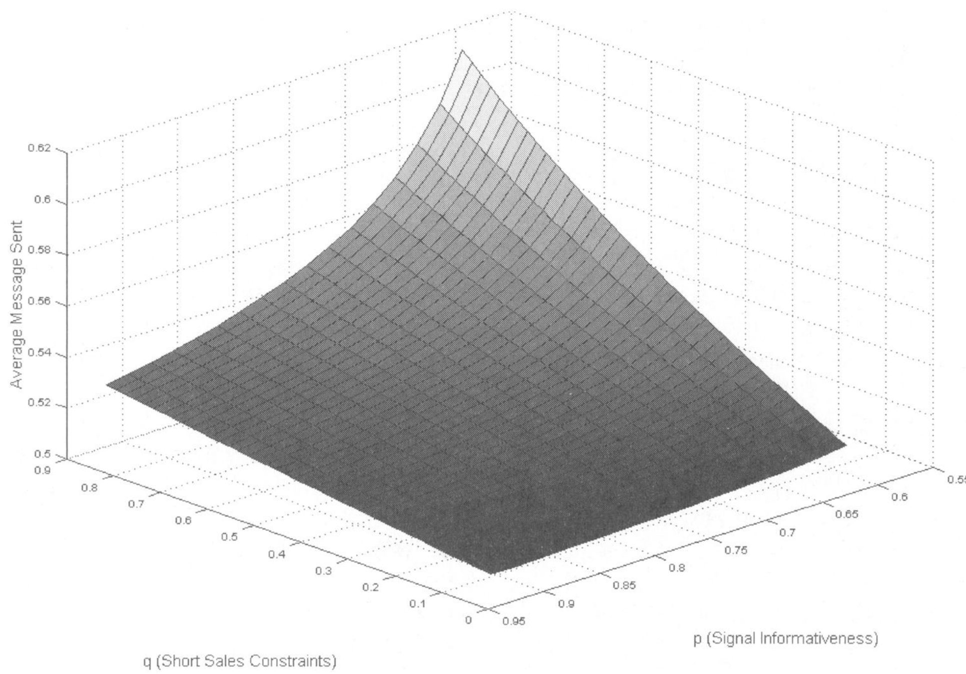

Figure 2. Average optimism comparative statics. This figure shows the average message sent in equilibrium for various combinations of p (signal informativeness) and q (short-sales constraints). The unbiased private signal has a value of 0.5, so this figure shows that optimism exists in equilibrium, and that optimism increases as p decreases and as q increases.

We can incorporate this version of the Spitzer view into our model by adding a simple modification.[33] Assume with probability ξ that the investor is naïve, in which case he believes that the analyst is always truthful, that is, he believes incorrectly that $\pi = 1$. With probability $1 - \xi$, assume that the investor is rational. We can then solve for the new equilibrium in this situation.

PROPOSITION 3: *If the investor is naïve (incorrectly believing that $\pi = 1$) with probability ξ, then the optimal strategy for the analyst is as follows.*

1. *An analyst with type $k \geq k^N$ always reports truthfully, sending the low message m_{low} when she receives the low private signal s_{low}, and sending the high message m_{high} when receiving the high private signal s_{high}. An analyst with type $k < k^N$ always reports the high message, irrespective of her private signal. The critical level of k^N is given by*

$$k^N = \frac{c\alpha(0.25 - (p-0.5)^2\theta^2)(0.25 - (p-0.5)^2\theta^2\pi^2)\left(q + (1-\xi)\left(\frac{\pi}{2-\pi} - 1\right)\right)}{(p-0.5)(1-\theta)\theta(2(0.25 - (p-0.5)^2\theta^2\pi^2)\xi + \pi(1+\pi)(0.25 - (p-0.5)^2\theta^2)(1-\xi))}, \tag{19}$$

[33] See Ottaviani and Squintani (2002) for a related model examining equilibria in a cheap talk game where some players act in a nonstrategic manner.

where $\pi = \Pr(k \geq k^N)$ is the probability that the analyst's type exceeds k^N.

2. *The equilibrium level of optimism is increasing in ξ.*

Proof of Proposition 3: See Appendix C.

Under the Spitzer model of investor irrationality, the equilibrium level of optimism is higher than it is with sophisticated investors. The intuition behind this result is that investors do not correctly adjust for the decreased credibility of a positive message relative to a negative message, so the asymmetry in trading volume between high and low messages facing the analyst is increased. Proposition 3 implies that the equilibrium level of optimism is higher when the proportion of naïve investors, ξ, is higher. Since the Spitzer view typically assumes that small investors are more prone to naïveté, a natural empirical implication is that equilibrium optimism should be higher for stocks with a larger proportion of retail investors.

Continuing our simple numerical example, with k uniform between 0 and 1, and parameters of $c = 0.05$, $\theta = 0.5$, $p = 0.60$, and $q = 0.5$, then the proportion of honest analysts is 90.58% when all investors are rational, 89.17% when 50% of investors are naïve, and 87.59% when all investors are naïve. The average message sent is 0.547, 0.554, and 0.562, respectively. Figure 3 plots the average message sent as a function of the proportion of naïve investors ξ. We can see that the message sent is increasing in ξ.

In summary, the model serves two purposes. First, it demonstrates that my three initial empirical findings can be generated by a simple model with fully rational agents in the presence of asymmetric information and short-sales constraints. Second, the model generates three further empirical predictions about the equilibrium level of optimism. The final section of the paper empirically tests these predictions.

V. Extension: Tests of Model Predictions

Proposition 2 predicts that the equilibrium level of optimism in analysts' forecasts should be increasing in the level of short-sales constraints, q, facing investors. As a proxy for q, I use stock size measured by the stock's percentile size rank (based on index-weight at the start of the year). Stock size is a reasonable proxy for two main reasons. First, smaller stocks are harder to physically short (e.g., D'Avolio (2002).[34] Second (and more importantly), most institutional funds are unable or unwilling to enter into short positions, (e.g., Almazan et al. (2004)). Given the neutral position of an institutional investor in a stock is equal to its benchmark index-weight, this leads to an asymmetric distribution of possible active positions. With constraints, negative information can only be

[34] D'Avolio (2002) finds that smaller stocks have higher average loan fees and are significantly more likely to be "on special," that is, they are periodically very expensive to borrow.

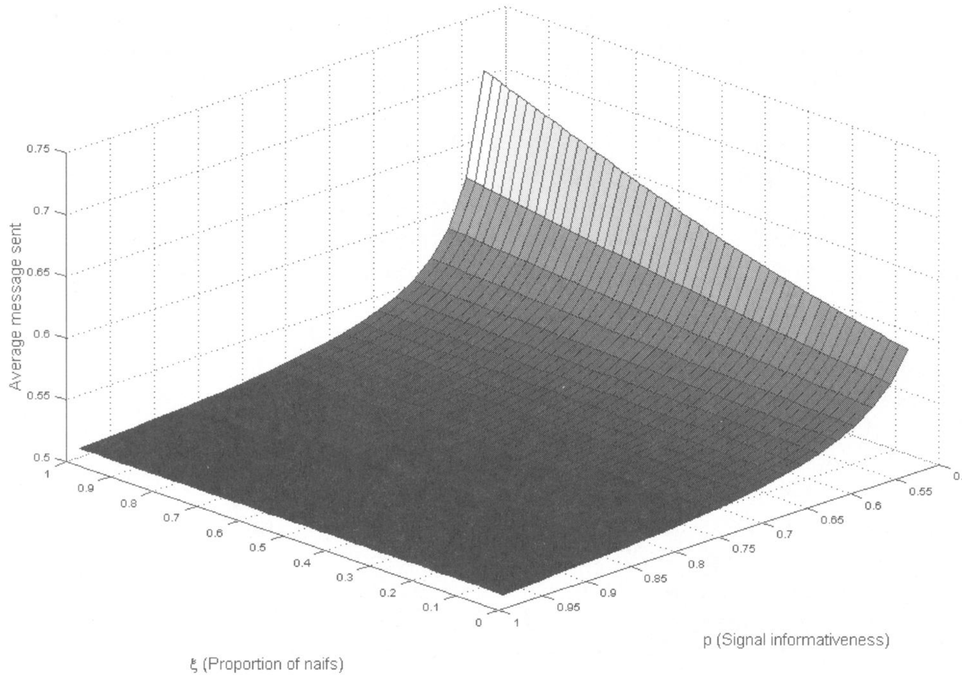

Figure 3. Average optimism comparative statics. This figure shows the average message sent in equilibrium for various combinations of p (signal informativeness) and ξ (proportion of naive investors). The unbiased private signal has a value of 0.5, so this figure shows that optimism exists in equilibrium, and that optimism increases as p decreases and as ξ increases.

incorporated downwards until zero stock is held, while positive positions may be incorporated up to multiple times index-weight. For large index-weight stocks, there is less asymmetry in this distribution of possible active positions than for smaller stocks.

The second comparative statics result from Proposition 2 is that equilibrium optimism is higher for stocks that have a lower difference in forecasting ability between high and low ability analysts, that is, low p stocks. The intuition behind this result is that analysts are less likely to be caught out if they cheat on a stock with earnings that are difficult to forecast. As a proxy for p, I use the dispersion of analyst forecasts (normalized by the stock price). Dispersion can be interpreted as a measure of the noise in the private signals received by analysts (e.g., Johnson (2004)), which fits naturally with our definition of p.

Proposition 3 predicts that equilibrium optimism is higher when the proportion of naïve investors increases. To proxy for naïve investors, in a manner consistent with the Spitzer view, I use the percentage of trading volume accounted for by retail investors in each stock. To test Proposition 3, we are therefore testing jointly our proxy for naïve investors plus the conjecture that optimism increases as the percentage of naïve investors increases.

The dependent variable required to test these three hypotheses is the average level of optimism in earnings forecasts for each stock. To measure this, each year for each stock, I calculate the consensus earnings forecast six months before the earnings announcement that falls in that year. The difference between the consensus and actual forecast is divided by the price at the time consensus is measured, to give an optimism measure. A positive optimism measure implies that the consensus forecast was higher than the actual earnings announcement. To ensure that the regression results are robust, I convert this measure to a percentile rank and do the same to each of the independent variables.

To test the three hypotheses, I run Fama–Macbeth regressions with consensus optimism as the dependent variable and with size, dispersion, and retail ownership as independent variables. In addition, to control for any effects of investment-banking on postdeal optimism, I include control variables indicating whether the stock had undertaken an IPO or SEO in the last 3 years and add a second control variable, analyst coverage.

Table VIII presents the regression results. In the univariate regressions, all three hypotheses appear to be supported, with significant t-statistics on size, dispersion, and retail share. However, in the multivariate regression, the retail-share coefficient becomes insignificant, while size and dispersion remain strong. Thus, the first two supplementary hypotheses are supported by the data. The third hypothesis is not strongly supported since we are unable to reject the null that the coefficient on retail share is zero. One reason for this result may be that small investors are not a good proxy for naiveté (as suggested by Jackson (2003)).

To ensure that these results are robust to my choice of proxy specification, I repeat the regressions using optimism measured three rather than six months prior to the earnings announcements. The results remain significant. I also repeat the multivariate regression separately for three subperiods. In each subperiod, the retail share variable is insignificant, while the size and dispersion variables remain highly significant in two of the three periods, and are marginally significant in the third. This result confirms that retail share is not robustly associated with consensus optimism. Next I repeat the tests, controlling for write-offs by first excluding stocks experiencing negative earnings in a given year, and second excluding stocks where earnings surprises exceed 5% of the stock price. Neither of these variations affects the results. As a final robustness check, to account for the forecast error distributional issues addressed by Abarbanell and Lehavy (2003), I calculate nonparametric estimates of consensus optimism differences. For small stocks (Ex-100), consensus forecasts exceed actual earnings in 63% of the cases, while for large stocks (top 50) this statistic is 49.7%. Similarly for high dispersion stocks (top quartile), consensus exceeds actual earnings in 65% of the cases, while for low dispersion stocks (bottom quartile) this statistic is 48%. The differences are highly significant, and confirm my earlier parametric results.

In summary, the model predicted higher levels of optimism for smaller and harder to forecast stocks and these predictions are verified in the data. An

Table VIII

Equilibrium Optimism Tests

This table analyzes the factors influencing the consensus level of optimism for a stock. *Optimism* is defined as the consensus forecast 6 months prior minus the actual earnings announcement normalized by the stock price. *Size Rank* is the size of the firm at the start of the year, expressed as a percentile rank. *Dispersion* is the dispersion of earnings forecasts 6 months prior to the actual earnings announcement. *Retail share* is the percentage of turnover accounted for by retail investors. *IPO* and *SEO* are dummy variables indicating whether the firm has undertaken an IPO or SEO in the last 3 years. *Coverage* measures the number of analysts covering the stock 6 months prior to the earnings announcement. Fama–Macbeth panel regressions are run annually for 9 yearly cross sections from 1994 to 2002. Average cross-sectional R^2 statistics are reported, as are the average number of observations in each cross section.

	Dependent Variable = Optimism (t)									
	(1)		(2)		(3)		(4)		(5)	
	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics	Coefficient	t-Statistics
Constant	0.639	31.54	0.379	14.63	0.420	24.43	0.503	8.04	0.546	11.54
Size rank	–0.235	–6.79					–0.181	–3.78	–0.238	–3.49
Dispersion			0.242	4.88			0.208	5.68	0.148	4.02
Retail share					0.227	4.11	0.011	0.21	–0.045	–1.13
SEO									0.005	0.41
IPO									–0.003	–0.14
Coverage									0.006	2.48
Average # in each cross section	204.6		205.3		205.3		204.6		204.6	
Average adjusted R^2	5.8%		7.6%		4.2%		11.8%		11.0%	

extension of the model (Proposition 3) allowed us to distinguish somewhat between the Spitzer and neoclassical explanations of the results. The findings tend to support the neoclassical view, which is consistent with the objective of the model, that is, to demonstrate that the empirical findings can be generated within a rational framework.

VI. Conclusion

This paper presents three main empirical findings. First, high reputation analysts generate higher future trading volume. Second, accurate analysts are rewarded with higher end-of-period reputations as measured by survey rankings. Third, optimistic analysts generate more trading volume for their brokerage firms.

To reconcile these results, I build a simple model to demonstrate that the incentive to generate trade may lead analysts to lie about their private signals. The analyst trades off an expected loss in reputation against the short-term benefit of higher trading commissions. In equilibrium, optimistic analysts indeed generate more short-term trading volume, even when investors are fully rational. However, as expected, an analyst's reputation suffers when she misleads investors. An analyst who cares highly about her future reputation refrains from opportunistic behavior.

I also confirm two auxiliary cross-sectional predictions from the model, namely that consensus optimism is higher when short-sales constraints are more likely to bind (proxied by firm size) and when process noise is higher (proxied by analyst dispersion). A third test to distinguish between behavioral and rational explanations of my findings supports the latter view, given that consensus optimism is not increasing in the proportion of retail investors in a stock.

These findings suggest that recent plans to split brokerage firms may be unsuccessful in eliminating analysts' optimism bias. Investment-banking incentives are likely to be replaced by trade-generation incentives, which ultimately generate a similar effect. However, the results do suggest that an analyst's concerns for her reputation may be a successful way to address excessive opportunism. Recent moves to make previous analyst forecasting track records more transparent increase the ability of investors (especially small investors) to form an opinion about the ability of the analyst. This increased reputation effect reduces the incentive of analysts to report untruthfully.

Extending the theoretical analysis to situations involving multiple analysts would be a fruitful area for future research, as would examining models in which the analyst is aware of whether the investor is short-sales constrained at any given point in time. Such models would generate more sophisticated patterns in analyst behavior, for example, engaging in flicking of forecasts in order to move clients in and out of a given stock over time. Other directions in which the model could be extended would be to incorporate multiple trading periods or to examine a richer state space for the asset payoff.

Appendix A: Proof of Proposition 1

In this appendix, I first derive the optimal beliefs and strategy of the investor, given the conjectured strategy of the analyst. Second, I verify that given the investor's beliefs and strategy the strategy of the analyst is indeed optimal. Finally, I discuss off-equilibrium beliefs.

A1. Optimal Investors' Beliefs

A1.1. Updating Rules About the State X

The analyst may be "smart," S, or "dumb", D. The analyst may also be "good," G, which means that her $k \geq k^*$, or "evil," E, if $k < k^*$. I denote the four possible analyst types as SG, SE, DG, and DE, respectively. In our posited equilibrium, good analysts report their private signal truthfully via either the high or low message, while evil analysts *always* report the high message. In addition, smart analysts receive informative private signals, while dumb analysts receive noise.

If the investor receives the low message m_L or the high message m_H, then he updates his beliefs about the state x using Bayes' rule accordingly as follows:

$$\lambda^*(m_L) = \Pr(x = x_H \mid m_L) = 0.5 - (p - 0.5)\theta \tag{A1a}$$

$$\lambda^*(m_H) = P(x = x_H \mid m_H) = 0.5 + (p - 0.5)\theta \left(\frac{\pi}{2 - \pi}\right). \tag{A1b}$$

We can see that $|\lambda^*(m_H) - \lambda| < |\lambda^*(m_L) - \lambda|$, namely, the low message induces a larger revision in belief since the investor knows this message only ever comes from a good analyst.

A1.2. Updating Rules About the Analyst's Type θ

At the end of the period, the investor compares the message sent by the analyst (either m_H or m_L) to the realized state of the world (x_H or x_L). The investor then updates his beliefs about the analyst's ability (i.e., the probability that the analyst is smart) using Bayes' rule. The four possible outcomes are outlined below. If the analyst sends a low message, the investor knows that this is truthful. If the analyst sends a high message, the investor must adjust his inference for the probability that the analyst is lying. A straightforward application of Bayes' rule yields the following results.

Case 1: Low message and low realized state

$$\begin{aligned} &P(\text{smart} \mid m_L \,\&\, x_L) \\ &= \frac{P(m_L \,\&\, x_L \mid \text{smart})P(\text{smart})}{P(m_L \,\&\, x_L \mid \text{smart})P(\text{smart}) + P(m_L \,\&\, x_L \mid \text{dumb})P(\text{dumb})} \\ &= \frac{p\theta}{0.5 + (p - 0.5)\theta}. \end{aligned} \tag{A2a}$$

Case 2: Low message and high realized state

$$P(\text{smart} \mid m_{\text{L}} \,\&\, x_{\text{H}}) = \frac{(1-p)\theta}{0.5-(p-0.5)\theta}. \tag{A2b}$$

Case 3: High message and high realized state

$$P(\text{smart} \mid m_{\text{H}} \,\&\, x_{\text{H}}) = \frac{(0.5+(p-0.5)\pi)\theta}{0.5+(p-0.5)\pi\theta}. \tag{A2c}$$

Case 4: High message and low realized state

$$P(\text{smart} \mid m_{\text{H}} \,\&\, x_{\text{L}}) = \frac{(0.5-(p-0.5)\pi)\theta}{0.5-(p-0.5)\pi\theta}. \tag{A2d}$$

A2. Investor's Desired Trade Size

At any given time, the investor chooses his shareholding $\delta = \delta(\lambda)$ to maximize expected utility as a function of his beliefs about the final state λ.

$$\max_{\delta} \lambda \ln(W + \delta(x_{\text{H}} - P_0)) + (1-\lambda)\ln(W + \delta(x_{\text{L}} - P_0)). \tag{A3}$$

The first-order condition gives the optimal holding as:

$$\delta(\lambda) = \frac{-W(\lambda(x_{\text{H}} - P_0) + (1-\lambda)(x_{\text{L}} - P_0))}{(x_{\text{L}} - P_0)\lambda + (x_{\text{H}} - P_0)(1-\lambda)}. \tag{A4}$$

Now the desired trade is the difference between $\delta(\lambda)$ and $\delta(\lambda^*)$. This is given as:

$$\delta(\lambda^*) - \delta(\lambda) = \alpha(\lambda^* - \lambda), \tag{A5}$$

where $\alpha = (-W(x_{\text{H}} - x_{\text{L}}))/((x_{\text{H}} - P_0)(x_{\text{L}} - P_0)) > 0$ since $x_{\text{L}} - P_0 < 0 < x_{\text{H}} - P_0$.

So the trade is directly proportional to the revision in the investor's beliefs $\lambda^* - \lambda$.

Given the presence of short-sales constraints, and the explicit results for the revision in investors beliefs, we can work out the expected trade sizes generated by a positive and a negative message.

For a positive message the actual (and expected) trade size is given as:

$$\text{Trade}(m_{\text{H}}) = \alpha\big(\lambda^*(m_{\text{H}}) - \lambda\big) = \alpha(p-0.5)\theta\left(\frac{\pi}{2-\pi}\right). \tag{A6}$$

For a negative message and nonbinding short-sales constraints, the trade size is given as:

$$\text{Trade}(m_{\text{L}} \mid \text{notbinding}) = \alpha\big(\lambda^*(m_{\text{L}}) - \lambda\big) = -\alpha(p-0.5)\theta. \tag{A7}$$

If the short-sales constraints are binding (with probability q), then the trade is zero.

Thus, the expected trade size from a negative message is given as:

$$E(\text{Trade}(m_{\rm L})) = -(1-q)\alpha(p-0.5)\theta. \tag{A8}$$

Finally, the expected difference in the absolute trade size between a positive and negative message is given as:

$$E(|\text{Trade}(m_{\rm high})| - |\text{Trade}(m_{\rm low})|) = \alpha(p-0.5)\theta\left(q + \left(\frac{\pi}{2-\pi}\right) - 1\right) > 0. \tag{A9}$$

Given that condition (13) holds, then the trade generated by a high message will be larger than the trade generated by a low message. This restriction implies that short-sales constraints are sufficiently large to offset the additional credibility of a low message.

A3. Analyst's Optimal Strategy

Given the beliefs and strategy of the investors, we now need to show that the analyst's strategy is indeed optimal. There are two possible cases. In the first case, the analyst receives a high private signal. In the second case, she receives a low private signal. We analyse the two situations as follows:

Case 1: When the analyst receives the high private signal, she reports the high private message irrespective of her type k. The intuition behind this result is straightforward. A high message generates higher trading volume. Additionally, a high message generates a higher expected end-of-period reputation θ^* since:

$$\begin{aligned} &E(\theta^* \mid m_{\rm H}, s_{\rm H}) = \theta \\ &E(\theta^* \mid m_{\rm L}, s_{\rm H}) = \frac{(0.5-(p-0.5)\theta)p\theta}{0.5+(p-0.5)\theta} + \frac{(0.5+(p-0.5)\theta)(1-p)\theta}{0.5-(p-0.5)\theta} < \theta. \end{aligned} \tag{A10}$$

Case 2: When the analyst receives the low private signal, the message she sends depends on her type. A high message generates more trading volume than a low signal; however, a low message generates a higher expected end-of-period reputation. So the analyst must trade off these two factors. The expected end-of-period reputation from the two messages is given by:

$$\begin{aligned} E(\theta^* \mid m_{\rm L}, s_{\rm L}) &= \theta \\ E(\theta^* \mid m_{\rm H}, s_{\rm L}) &= \frac{(0.5-(p-0.5)\theta)(0.5+(p-0.5)\pi)\theta}{0.5+(p-0.5)\pi\theta} \\ &\quad + \frac{(0.5+(p-0.5)\theta)(0.5-(p-0.5)\pi)\theta}{0.5-\pi\theta} < \theta. \end{aligned} \tag{A11}$$

The expected loss in reputation from lying is given by:

$$E(\theta^* \mid s_{\rm L}, m_{\rm L}) - E(\theta^* \mid s_{\rm L}, m_{\rm H}) = \frac{\theta^2(1-\theta)(p-0.5)^2\pi(1+\pi)}{0.25-(p-0.5)^2\theta^2\pi^2} > 0. \tag{A12}$$

From equation (12) in the text we can see that the analyst tells the truth if k is sufficiently large. There exists a critical level of k, given by k^*, at which the analyst is indifferent between reporting the high or low message. This critical value of k is given by solving equation (12) and equals:

$$k^* = \frac{c\alpha\left(\frac{\pi}{2-\pi} + q - 1\right)(0.25 - (p-0.5)^2\theta^2\pi^2)}{\pi(1+\pi)(p-0.5)(1-\theta)\theta}. \tag{A13}$$

If the analyst is of type $k \geq k^*$ she truthfully reports the low message. If her type is $k < k^*$ then she lies and reports the *high* message. The probability that the analyst is honest is given by $\pi = \Pr(k \geq k^*)$. The analyst type k is distributed on $[0, \infty)$ according to the distribution function $F(k)$. Given a specific distribution function, we can express π in terms of the underlying model parameters. However, for our purposes it is not necessary to specify a particular $F(k)$ so long as it has some mass to either side of the critical value of k^*.

A4. Other Considerations

We have shown that the investor's beliefs and strategy are optimal given the analyst's strategy. Also the analyst's strategy is optimal given the investor's beliefs and strategy. In this model, we do not need to check the investor's off-equilibrium beliefs since all the information sets of the investor are reached with positive probability. As such, it is sufficient to show that the investor uses Bayes' law to update beliefs at each of his information sets, which he indeed does. Thus, the equilibrium is a perfect Bayesian equilibrium which, given the previous sentence, implies that it is equivalent to the weak perfect Bayesian equilibrium of this game.

A5. Derivation of Equilibrium Outcomes

Outcome 1: It is straightforward to show that $(\partial(\delta_2^{\mathrm{H}} - \delta_1))/\partial\theta > 0$ and $(\partial(-\delta_2^{\mathrm{L}} + \delta_1))/\partial\theta > 0$. Thus, higher reputation analysts generate higher trading volume.

Outcome 2: Since

$$P(\text{smart} \mid m_{\mathrm{L}}, x_{\mathrm{L}}) > P(\text{smart} \mid m_{\mathrm{H}}, x_{\mathrm{H}}) > P(\text{smart} \mid m_{\mathrm{H}}, x_{\mathrm{L}}) > P(\text{smart} \mid m_{\mathrm{L}}, x_{\mathrm{H}}),$$

we can see that if the analyst's message is ex post correct, that is, $m = x$, her posterior reputation will be higher.

Outcome 3: See equation (A9).

Outcome 4: The average message sent in equilibrium is given as:

$$E(m) = P(\text{good})(0.5(0) + 0.5(1)) + P(\text{evil})(0(0) + 1(1)) = 1 - 0.5\pi. \tag{A14}$$

Appendix B: Proof of Proposition 2

Given (A13), we want to prove the two partial derivative results in Proposition 2. To enable an analytic solution,[35] assume that k is uniformly distributed. Then we have $\pi = 1 - k$. Define two new variables, $s = \theta(2p - 1)$ and $\gamma = c\alpha/(2(1-\theta))$, then (A13) simplifies to:

$$k = \frac{\gamma(q + kq - 2k)(1 - s^2(1-k)^2)}{s(1+k)(1-k)(2-k)}. \tag{B1}$$

Define the function $F(k, q, s)$ as

$$F(k,q,s) = sk(1+k)(1-k)(2-k) - \gamma(q + kq - 2k)(1 - s^2(1-k)^2). \tag{B2}$$

Then equation (A13) is equivalent to $F(k, q, s) = 0$. To prove our result, we first need to prove the following lemma.

LEMMA B1: If $F(k, q, s) = 0$, *then* $(\partial F/\partial k)(k,q,s) > 0$.

Proof of Lemma B1: Differentiating (8) we get:

$$\begin{aligned}\frac{\partial F}{\partial k}(k,q,s) &= 2s(1 - k - 3k^2 + 2k^3)\\ &\quad -\gamma(q - 2 + s^2(1-k)(2 + 3kq - 6k + q)).\end{aligned} \tag{B3}$$

Also we can solve equation (B2) for γ using $F(k, q, s) = 0$ to get:

$$\gamma = \frac{sk(1+k)(1-k)(2-k)}{(q + kq - 2k)(1 - s^2(1-k))}. \tag{B4}$$

Substituting this into (B3) gives:

$$\begin{aligned}\frac{\partial F}{\partial k}(k,\ q,\ s) &= 2s(1 - k - 3k^2 + 2k^3) - \frac{sk(1+k)(1-k)(2-k)}{(q + kq - 2k)(1 - s^2(1-k)^2)}\\ &\quad \times (q - 2 + s^2(1-k)(2 + 3kq - 6k + q)).\end{aligned} \tag{B5}$$

This is positive if and only if:

$$\begin{aligned}&2(1 - k - 3k^2 + 2k^3)(q + kq - 2k)(1 - s^2(1-k)^2)\\ &\quad > k(1+k)(1-k)(2-k)(q - 2 + s^2(1-k)(2 + 3kq - 6k + q)).\end{aligned} \tag{B6}$$

Since q enters this expression only linearly, the inequality is true for all values of q if it is true for the values $q = 0$ and $q = 1$. To see this, the inequality can be written as $qS > T$, so if $0 > T$ and $S > T$, then $qS > T$ for $0 < q < 1$. The variable s enters the equation only in the form s^2 so we can use the same argument. If

[35] I thank Michael Ulm for significant assistance in analytically proving this result and Harjoat Bharmra for valuable suggestions.

the inequality holds for $s = 0$ and $s = 1$, then it holds for all s. So we need to consider four cases.

Case 1: $q = 0, s = 0$. Inequality (B6) simplifies to:

$$2(1 - k - 3k^2 + 2k^3)(-2k) > k(1 + k)(1 - k)(2 - k)(-2), \tag{B7}$$

or $2k^2(1 + 4k - 3k^2) > 0$, which is clearly true since $0 \leq k < 1$.

Case 2: $q = 0, s = 1$. Inequality (B6) simplifies to:

$$2k^2(k - 2)^2(1 + k^2) > 0, \tag{B8}$$

which is true.

Case 3: $q = 1, s = 0$. Inequality (B6) simplifies to:

$$(1 - k)^2(2 + 2k - 3k^2) > 0, \tag{B9}$$

which is true.

Case 4: $q = 1, s = 0$. Inequality (B6) simplifies to:

$$k^2(1 - k)^2(2 - k)^2 > 0, \tag{B10}$$

which is true.

So the inequality is true for all relevant values of q, s. Thus, the lemma holds. Q.E.D.

Using this lemma it is straightforward to prove Proposition 2. By the implicit function theorem we have:

$$\frac{\partial k}{\partial q} = -\frac{\partial F/\partial q}{\partial F/\partial k}, \tag{B11}$$

and since: $(\partial F/\partial q) = -\gamma(1 - k)(1 - s^2(1 - k)^2) < 0$, and by the lemma, $(\partial F/\partial k) > 0$.

Combining these results, we get $(\partial k/\partial q) > 0$ as required for Proposition 2.1. Similarly,

$$\frac{\partial k}{\partial s} = -\frac{\partial F/\partial s}{\partial F/\partial k}. \tag{B12}$$

Now since $(\partial F/\partial s) = k(1 + k)(1 - k)(2 - k) + 2s\gamma(q + kq - 2k)(1 - k)^2 > 0$ and by the lemma $(\partial F/\partial k) > 0$.

Combining these results, we get $(\partial k/\partial s) < 0$.

Finally, since $s = \theta(2p - 1)$, we get $(\partial k/\partial p) < 0$ as required for Proposition 2.2. Q.E.D.

Appendix C: Proof of Proposition 3

To prove this proposition we need to modify the results from Proposition 1 to account for the fact that with some probability, the investor is naïve. The proof is identical to Proposition 1; however, now the analyst faces a naïve investor with probability ξ. With probability $1-\xi$, she faces a rational investor (who is aware that the naïve investor also exists).

The rational investor has a belief π that the analyst is a "good" analyst. The analyst faces the following trade-off between short-term gains in commission from a high message versus an expected loss in reputation. The short-term gain in commission now becomes:

$$E(\text{Trade} \mid m_{\text{H}}) - E(\text{Trade} \mid m_{\text{L}}) = \alpha(p-0.5)\theta\left(q + (1-\xi)\left(\frac{\pi}{2-\pi} - 1\right)\right). \quad \text{(C1)}$$

The expected loss in reputation becomes:

$$E\left(\theta^* \mid m_{\text{L}}\right) - E\left(\theta^* \mid m_{\text{H}}\right)$$
$$= \frac{\theta^2(1-\theta)(p-0.5)^2(2(0.25-(p-0.5)^2\theta^2\pi^2)\xi + \pi(1+\pi)(0.25-(p-0.5)^2\theta^2)(1-\xi))}{(0.25-(p-0.5)^2\theta^2)(0.25-(p-0.5)^2\theta^2\pi^2)}. \quad \text{(C2)}$$

The critical level k^N at which the analyst is indifferent between the two messages is:

$$k^N = \frac{c\alpha(0.25-(p-0.5)^2\theta^2)(0.25-(p-0.5)^2\theta^2\pi^2)\left(q + (1-\xi)\left(\frac{\pi}{2-\pi} - 1\right)\right)}{\theta(1+\theta)(p-0.5)(2(0.25-(p-0.5)^2\theta^2\pi^2)\xi + \pi(1+\pi)(0.25-(p-0.5)^2\theta^2)(1-\xi))}. \quad \text{(C3)}$$

This replaces the previous critical level k^* and the results otherwise are identical. The naïve investor behaves like the investor in Proposition 1 with $\pi = 1$. The rational investor here behaves like the investor in Proposition 1, but replaces k^* with k^N when forming his beliefs.

We now move to proving the second part of Proposition 3, namely that $(\partial k^N/\partial \xi) > 0$.

Let $s = \theta(2p-1) > 0$ and $\gamma = (c\alpha(0.25-(p-0.5)^2\theta^2))/(\theta(1-\theta)(p-0.5)) > 0$, then we can simplify (C3) to the following expression.

$$\begin{aligned} F(s,k,\xi) &= k(1+k)2(1-s^2(1-k)^2)\xi \\ &\quad + k(1+k)(1-k)(2-k)(1-s^2)(1-\xi) \\ &\quad - \gamma(1-s^2(1-k)^2)((1+k)q - (1-\xi)2k) = 0 \end{aligned} \quad \text{(C4)}$$

or alternatively,

$$\begin{aligned} F(s,k,\xi) &= q(s^2-1)\gamma - k[-2 + s^2(2+\gamma(2+q-2\xi)) + \gamma(-2+q+2\xi)] \\ &\quad + k^2[-1+3\xi+s^2(1+\xi-\gamma(q-4+4\xi))] \\ &\quad + k^3[2(\xi-1)+s^2(2+\gamma(-2+q+2\xi))] \\ &\quad - k^4[-1+\xi+s^2(1+\xi)] = 0. \end{aligned} \quad \text{(C5)}$$

Differentiation yields,

$$
\begin{aligned}
\frac{\partial F}{\partial k} &= 2 - s^2(2+\gamma(2+q-2\xi)) - \gamma(-2+q+2\xi) \\
&\quad + 2k[-1+3\xi+s^2(1+\xi-\gamma(-4+q+4\xi))] \\
&\quad + 3k^2[2(\xi-1)+s^2(2+\gamma(-2+q+2\xi))] \\
&\quad - 4k^3[-1+\xi+s^2(1+\xi)] > 0 \qquad \text{(C6)}
\end{aligned}
$$

and

$$
\begin{aligned}
\frac{\partial F}{\partial \xi} &= -k[3+s^2(1-4\gamma)] + k^2[3+s^2(1-4\gamma)] \\
&\quad + k^3[2+2s^2\gamma] - k^4[1+s^2] < 0. \qquad \text{(C7)}
\end{aligned}
$$

Implicit differentiation therefore yields

$$\frac{\partial k}{\partial \xi} = -\frac{\partial F/\partial k}{\partial F/\partial \xi} > 0, \qquad \text{(C8)}$$

as required. Q.E.D.

Appendix D: Calculation of Cluster-Adjusted *t*-Statistics

In the pooled regressions, the same analyst produces earnings estimates for several stocks in a given year. This potentially implies that observations within a single analyst–year cluster are correlated, if common shocks affect all stocks covered by the analyst in a similar way. More generally in the presence of clustering, the observations within a cluster may not be treated as independent, even though the clusters themselves may be considered independent. The detailed calculation of the covariance matrix allowing for clustering is given as follows, comparing it to the OLS estimator and to the White estimator. Further details are available in Williams (2000).

OLS variance estimator

$$V_{\text{OLS}} = s^2(X'X)^{-1} \qquad \text{(D1)}$$

where

$$s^2 = \frac{1}{(N-k)}\sum_{i=1}^{N} e_i^2.$$

Robust (White) unclustered variance estimator

$$V_{\text{rob}} = (X'X)^{-1}\left[\sum_{j=1}^{n}(e_i x_i)'(e_i x_i)\right](X'X)^{-1}. \qquad \text{(D2)}$$

Robust cluster variance estimator

$$V_{\text{cluster}} = (X'X)^{-1}\left[\sum_{j=1}^{n_C} u'_j u_j\right](X'X)^{-1}, \tag{D3}$$

where

$$u_j = \sum_{j_{\text{cluster}}} e_i x_i.$$

In the calculations, e_i is the i^{th} residual and x_i is a row vector of predictors. The variance of the clustered estimator is higher than the robust estimator when there is positive correlation between elements of the cluster. Positive correlation means the cluster sums have more variability than the individual elements. Negative correlation within a cluster has the reverse effect.

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