Do Analyst Conflicts Matter?
Evidence from Stock Recommendations

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Comments welcome

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Abstract

We examine whether conflicts of interest with investment banking and brokerage induce sell-side analysts to issue optimistic stock recommendations, and if so, whether investors are misled by such biases. Using quantitative measures of potential conflicts constructed from the revenue components of analyst employers, we find that the level of analysts' stock recommendations is indeed positively related to the magnitude of conflicts they face. We also find that the optimistic bias stemming from investment banking conflict was especially pronounced during the late-1990s stock market bubble. However, evidence from the response of stock prices and trading volumes to upgrades and downgrades suggests that the market recognizes analyst conflicts and properly discounts analyst opinions. This pattern is more pronounced during the bubble period, contrary to popular belief that investors threw caution to the wind during the bubble. Moreover, the one-year performance of revised recommendations is unrelated to the magnitude of conflicts. Overall, our findings do not support the view that conflicted analysts are able to systematically mislead investors with optimistic stock recommendations.

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

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

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In April 2003, ten of the largest Wall Street firms reached a landmark settlement with state and federal securities regulators on the issue of conflicts of interest faced by stock analysts. The settlement requires the firms to pay a record $1.4 billion in compensation and penalties in response to government charges that the firms issued optimistic stock research to win favor with potential investment banking clients. Part of the settlement funds are earmarked for investor education and for the provision of stock research from independent firms. In addition to requiring large monetary payments, the settlement mandates structural changes in the firms' research operations and requires the firms to disclose conflicts of interest in analysts' research reports.

The notion that investors are victims of biased stock research presumes that (1) analysts respond to the conflicts by inflating their stock recommendations, and (2) investors take analysts' recommendations at face value. Even if analysts are biased, it is possible that investors understand the conflicts of interest inherent in stock research and rationally discount analysts' opinions. This alternative viewpoint, if accurate, would lead to very different conclusions about the consequences of analyst research. Indeed, investor rationality and self-interested behavior imply that stock prices should accurately reflect a consensus about the informational quality of public announcements (see Grossman (1976) and Grossman and Stiglitz (1980)). Rational investors would recognize and adjust for analysts' potential conflicts of interest, largely avoiding the adverse consequences of biased stock recommendations.

In this paper, we provide evidence on the extent to which analysts and investors respond to conflicts of interest in stock research. We address four questions. First, is the extent of optimism in stock recommendations related to the magnitudes of analysts' conflicts of interest? Second, to what extent do investors discount the opinions of more conflicted analysts? In particular, do stock prices and trading volumes react to recommendation revisions in a manner that rationally reflects the degree of analyst conflicts? Third, is the medium-term (i.e., three- to twelve-month) performance of recommendation revisions related to conflict severity? And finally, do conflicts of interest affect analysts and investors differently between the late 1990s stock bubble and the post-bubble period? The answers to these questions are clearly of relevance to stock market participants, regulators, and the academic profession.

Our empirical investigation makes use of a unique, hand-collected dataset that contains the annual revenue breakdown for 232 public and private analyst employers. This information allows us to construct quantitative measures of the magnitude of potential conflicts not only from investment banking, but also from brokerage business.[1] We analyze a sample of over 110,000 stock recommendations issued by over 4,000 analysts during the 1994-2003 time period. Using univariate tests as well as cross-sectional regressions that control for size of the followed company and individual analysts' experience, resources, workloads, and reputations, we attempt to shed light both on how analysts respond to pressures from investment banking and brokerage and on how investors compensate for the existence of such conflicts of interest.

A number of previous studies (e.g., Dugar and Nathan (1995), Lin and McNichols (1998), Michaely and Womack (1999), Dechcow, Hutton, and Sloan (2000), and Bradley, Jordan, and Ritter (2004)) have focused on conflicts faced by analysts in the context of existing underwriting relationships. Our paper complements this recent and growing literature in several ways. First, our approach takes into account the pressure to generate underwriting business from both current and potential client companies. Even if an analyst's firm does not currently do IB business with a company that the analyst tracks, it might like to do so in the future. Second, we examine the conflict of interest with investment banking in general, rather than solely from underwriting. In addition to underwriting securities offerings, investment banks provide advisory services on mergers, restructuring, and other corporate control matters. These revenue-generating activities may give rise to additional pressures on analysts. Third, we examine conflicts arising

[1]Concurrent research by Barber, Lehavy and Trueman (2004) and Clarke, et al. (2004) examines the short-term and medium-term stock price response to recommendations of conflicted analysts by classifying securities firms into investment banks, brokerages and research firms. Malmendier and Shanthikumar (2004) separately examine the trading response of small and large investors to recommendations by analysts facing IB conflicts, by classifying firms into underwriters and others. In contrast, we use data on the revenue breakdown of analyst employers to gauge the magnitude of potential conflicts rather than just their presence.

from brokerage business in addition to those from IB.[2] Fourth, the prior empirical finding that underwriter analysts are more optimistic is subject to the alternative interpretation that a company picks an underwriter whose analyst likes the stock to begin with. By examining all recommendation revisions made by a large cross-section of analysts, our approach sidesteps this issue of selection bias. Finally, our approach yields substantially larger sample sizes than prior research, leading to greater statistical reliability of the results. The present work complements Agrawal and Chen (2004), which employs a similar approach to study the relation between conflicts of interest and the quality of analysts' earnings forecasts and long-term growth projections.

We find that analysts do indeed seem to respond to pressures from investment banking and brokerage: larger potential conflicts of interest from these businesses are associated with more positively-biased recommendation levels. We also document that the distortive effects of investment banking were larger during the late-1990s stock bubble than during the post-bubble period. Nonetheless, the empirical analysis yields several pieces of evidence to suggest that investors are sophisticated enough to adjust for these biases. First, the short-term reactions of both stock prices and trading volumes to recommendation upgrades are significantly negatively related to the magnitudes of potential IB or brokerage conflicts. For downgrades, the corresponding relation is negative for stock prices but positive for trading volume. Second, the one-year investment performance of recommendation revisions bears no systematic relationship with the magnitude of conflicts. Finally, investors appear to have discounted analyst opinions more heavily during the bubble period, when conflicts were likely more severe, than during the post-bubble period. Altogether, these results strongly support the idea that investors rationally discount stock recommendations in accordance with analysts' conflicts.

The remainder of the paper is organized as follows. We discuss the issues in section 2 and describe our sample and data in section 3. Section 4 deals with the relation between recommendation levels and the degree of IB or brokerage conflict faced by

[2]Hayes (1998) theoretically analyzes how pressure on analysts to generate brokerage commissions affects the availability and accuracy of earnings forecasts. Both Irvine (2004) and Jackson (2005) find that analyst optimism increases a brokerage firm's share of trading volume. However, these papers do not examine how investor response to analyst recommendations and investment performance of recommendations vary with the severity of brokerage conflicts, issues that we investigate here.

analysts. Section 5 analyzes how conflicts are related to the response of stock prices and trading volume to recommendation revisions. Section 6 investigates the relation between conflicts and the investment performance of recommendation revisions. Section 7 presents our results for the late 1990s stock bubble and post-bubble periods, and section 8 concludes.

2. Issues and hypotheses

In this section, we discuss the primary conflicts of interest that sell-side analysts are likely to face within diversified securities firms, and we develop two competing hypotheses concerning how investors respond to recommendations in the presence of such conflicts.

Investment banking activity is one potential source of analyst conflict that has received widespread attention in the financial media (e.g., Gasparino (2002) and Maremont and Bray (2004)) as well as the academic literature (e.g., Lin and McNichols (1998) and Michaely and Womack (1999)). When IB business is an important source of revenue for a securities firm, a stock analyst employed by the firm may face pressure to inflate his recommendations. This pressure is due to the fact that the firm may seek to sell investment banking services to a company that the analyst tracks.[3] The company, in turn, would like the analyst to support its stock with a favorable opinion.[4] Thus, we expect that the more critical is investment banking revenue to an analyst's employer, the greater the incentives an analyst faces to issue optimistic recommendations.[5]

An analyst also faces a potential conflict with his employer's brokerage business. Here, the pressure on the analyst originates not from the companies that he follows, but from within his firm. Brokerage trading generates a large portion of most securities firms' revenues, and analyst compensation schemes are typically related explicitly or implicitly to trading commissions. Thus, analysts have incentives to increase trading volume in both

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

[4]Ljungqvist, et al. (2004) analyze the interaction between IB conflicts and institutional ownership.

[5]With short-term earnings forecasts, a company sometimes wants an analyst to be pessimistic in order to lower the market's expectations, allowing the company to meet or beat those expectations. But with stock recommendations, there is no reason for a company to want the analyst to be pessimistic.

directions (i.e., buys and sells). Given the many institutional constraints that make short sales relatively costly, a much larger set of investors participates in stock purchases as compared to stock sales.[6] Indeed, it is mostly existing shareholders of a stock who sell. This asymmetry between purchases and sales implies that the more important is brokerage business to an analyst's employer, the more pressure the analyst faces to be bullish in his recommendations.

Conflicts of interest with investment banking and brokerage may be kept in check by an analyst's career concerns. An analyst who responds to the conflicts he faces by issuing blatantly misleading stock recommendations can develop a bad reputation that reduces his labor income and hurts his career.[7] Stock recommendations, however, are not as easily evaluated as other outputs of analyst research such as 12-month price targets or quarterly earnings forecasts, which can be judged against public, near-term realizations. Therefore, career concerns may not completely prevent the analyst from responding to pressures to generate IB or brokerage business.

The relation between the market impact of an analyst's recommendations and the degree of conflict faced by the analyst should depend upon whether investors rationally discount or naively follow the opinions of conflicted analysts.[8] Under the *rational discounting hypothesis*, this relation should be asymmetric for upgrades and downgrades. For upgrades, the stock price response should be negatively related to the degree of conflict. This is due to the fact that analysts who face greater pressure from IB or brokerage are likely to be more bullish in their recommendations, and rational investors should discount an analyst's optimism more heavily. For downgrades, however, the story is somewhat different. When an analyst downgrades a stock despite facing large conflicts, rational investors should find the negative opinion more convincing and should be more

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[6]Numerous regulations in the United States increase the cost of selling shares short (see, e.g., Dechow, Hutton, Meulbroek and Sloan (2001)). Therefore the vast majority of stock sales are regular sales rather than short sales. For example, over the 1994-2001 period, short sales comprised only about ten percent of the annual New York Stock Exchange trading volume (see NYSE (2002)).

[7]See, e.g., Jackson (2005) for a theoretical model showing that analyst concerns about reputation can reduce optimistic biases arising from brokerage business.

[8]This framework follows Kroszner and Rajan (1994) and Gompers and Lerner (1999), who analyze the conflicts that a bank faces in underwriting securities of a company, when the bank owns a (debt or equity) stake in it.

likely to revalue the stock accordingly. This implies that the stock price response to a downgrade should be negatively related to the degree of conflict.

The rational discounting hypothesis also predicts cross-sectional relationships between conflict severity and the trading volume impact of upgrades and downgrades. As Kim and Verrecchia (1991) demonstrate in a rational expectations model of trading, the more precise a piece of news, the more individuals will revise their prior beliefs and hence the more trading that will result. In the present context, investor rationality implies that upgrades by highly conflicted analysts represent less precise news to investors, and so such revisions should be followed by relatively small abnormal volume. But when an analyst downgrades a stock in spite of greater conflicts, the public signal is regarded as being more precise, and thus the downgrade should lead to relatively large abnormal trading.

By contrast, under the *naïve investor hypothesis*, investors are largely ignorant of the distortive pressures that analysts face, and the market accepts analysts' recommendations at face value. This implies that there should be no relation between conflict severity and the response of either stock prices or trading volume to recommendation revisions. Furthermore, the absence of a systematic relationship should hold true for both upgrades and downgrades.

What are the implications of the two hypotheses for the medium-term (3 to 12-month) investment performance of analyst recommendations? Under the rational discounting hypothesis, there should be no systematic relation between analyst conflicts and investment performance: the market correctly anticipates the potential distortions upfront and accordingly adjusts its response. But the naïve investor hypothesis predicts that performance should be negatively related to conflict severity for both upgrades and downgrades. That is, investors ignore the conflict upfront and pay for their ignorance later on.

3. Sample and data

We describe our sample in section 3.1 and characteristics of analysts, their employers, and the companies they follow in section 3.2.

3.1. Sample

We obtain our sample of stock recommendations from the I/B/E/S U.S. Detail Recommendations History file. This file contains data on newly issued recommendations as well as revisions and reiterations of existing recommendations made by individual analysts over the period from 1993 to 2003. Although the exact wording of recommendations can vary considerably across brokerage houses, I/B/E/S classifies all recommendations into five categories ranging from *strong buy* to *strong sell*. We rely on the I/B/E/S classification, encoding recommendations on a numerical scale from 5 (*strong buy*) to 1 (*strong sell*). We use the I/B/E/S Stopped Recommendations file to determine instances where a brokerage firm dropped coverage of a company.[9]

Since we are primarily interested in examining how the nature and consequences of analyst recommendations are related to investment banking or brokerage businesses, we require measures of the importance of these business lines to analysts' employers. Under U.S. law, all registered broker-dealer firms must file audited annual financial statements with the Securities and Exchange Commission (SEC).[10] Such filings, referred to as x-17a-5 filings, must contain information on broker-dealer firms' principal sources of revenue. We use these filings to obtain various financial data, including data on our key explanatory variables: the fraction of total brokerage house revenues from either investment banking or brokerage commissions. Beginning with the names of analyst employers contained in the I/B/E/S Broker Translation file, we search for all available revenue information in x-17a-5 filings from 1994 to 2003.[11] For publicly traded broker-dealer firms, we also use 10-K annual report filings over the sample period to gather information on revenue breakdown, if necessary. We thus obtain annual data from 1994 to 2003 on investment banking revenue, brokerage revenue, and total revenue for 188 privately held and 44 publicly-traded

[9]This file contains numerous cases where an analyst 'stops' coverage of a stock, only to issue a new recommendation a month or two later. Conversations with I/B/E/S representatives indicate that such events likely represent pauses in coverage due to company quiet periods or analyst reassignments within a brokerage house. We define a stopped coverage event to be a true stoppage only if the analyst does not issue a recommendation on the stock over the subsequent six months.

[10]The Securities Exchange Act, sections 17 (a) through 17 (e).

[11]The electronic availability of x-17a-5 filings is very limited prior to 1994, the year the SEC first mandated electronic form filing. Hence, we do not search for revenue information prior to 1994.

brokerage houses.[12] For each brokerage house, we match recommendations to the latest broker-year revenue data preceding the recommendation date. Over the sample period, we are able to match in this fashion 110,493 I/B/E/S recommendations issued by 4,089 analysts.

A brokerage firm can withhold the public disclosure of revenue breakdown information in its x-17a-5 filing if, according to the SEC, there are reasonable grounds to believe that such disclosure would harm its competitive position. Thus, our sample of private securities firms is limited to broker-dealers that chose to disclose their revenue breakdown in x-17a-5 filings. We examine whether this selection bias affects our results by separately analyzing the sub-sample of publicly traded securities firms, for which public disclosure of revenue information in 10K annual reports is mandatory. Our findings do not appear to be affected by this selection bias. All our results for the sub-sample of publicly traded securities firms are qualitatively similar to the results for the full sample reported in the paper.

3.2 Characteristics of analysts, their employers, and companies followed

In addition to constructing revenue-based measures of potential conflict from investment banking and brokerage businesses, we assemble a number of explanatory variables designed to capture characteristics of analysts, their employers, and the companies they cover.

From the I/B/E/S detail history files, we construct variables that capture analysts' research experience and workloads. These characteristics may influence the accuracy and credibility of analyst research (see, e.g., Clement (1999), and Jacob, Lys, and Neale (1999)). Since analyst-level recommendations do not appear in the dataset prior to October 1993, we measure an analyst's research experience in terms of all of her research activity reported on I/B/E/S, including long-term earnings growth (LTG) forecasts and quarterly and annual earnings-per-share (EPS) forecasts. Thus we are able to measure analyst experience beginning in January 1981. General research experience is measured as the number of days since an analyst first appeared in the I/B/E/S database. We also employ a measure of company-specific research experience: the number of days since an

[12]We exclude a small number of firm-years in which total revenue is negative (e.g., due to losses from proprietary trading).

analyst first issued I/B/E/S research on a particular company. To capture analysts' workloads, we compute the number of different companies and the number of different 4-digit I/B/E/S S/I/G industry groups[13] for which an analyst issued recommendations in a particular calendar year.

The size of resources devoted to investment research within brokerage houses may also affect the quality of analysts' research (Clement (1999)). Larger houses may have better technology, better access to information and better support staffs. Accordingly, we use data on three measures of brokerage house size: the number of analysts issuing stock recommendations for a brokerage house over the course of a calendar year, book value of total assets, and net sales.

To capture the degree to which investors may believe that individual analysts have skill in providing timely and accurate research, we use two measures of analyst reputation. The first is based upon *Institutional Investor* (*II*) magazine's survey of *All-American* analysts. Each year on October 15, *II* mails an issue to subscribers listing the names of analysts that receive the most votes in a poll of institutional money managers. About 300 to 400 analysts are identified. We construct a variable that indicates, for each recommendation revision, whether the recommending analyst was named to the first, second, third, or honorable mention team in the latest annual *All-American* survey.

As a complementary, objective measure of analyst reputation, we use a variable based on the *Wall Street Journal*'s annual *All-Star* survey of analysts. Membership on the *WSJ All-Star* team is determined by an explicit set of criteria relating to past stock-picking performance and forecasting accuracy.[14] The survey includes about 50 industries annually and names the top five stock pickers and top five earnings forecasters in each industry.

Since the I/B/E/S Broker Translation File only provides analysts' last names and first initials, in some instances it is not possible to ascertain from I/B/E/S data alone whether

[13]I/B/E/S Sector/Industry/Group (S/I/G) numbers are six-digit codes that provide information on the industry sectors and sub-sectors for companies in the I/B/E/S database. We use the first four digits, which correspond to broad industry groupings.

[14]We recognize that the performance metrics used in the *WSJ All-Star* survey are public information and can, in principle, be replicated by investors. However, to the extent that computing and evaluating analyst performance is a costly activity, being named to the *All-Star* team may still affect an analyst's reputation and credibility.

or not an analyst in our sample was named to the *II* or *WSJ* teams. For these cases, we determine team membership of analysts using *NASD BrokerCheck*[15], an online database that provides the full names of registered securities professionals as well as their employment and registration histories for the past ten years. The database also keeps track of analyst name changes (e.g., resulting from marriage).

Table 1 provides a summary overview of the characteristics of our sample. In Panel A, the mean and median percentages of analyst employer revenues derived from investment banking (IB%) or from brokerage business (COM%) are reported for each of the five recommendation categories. Both the mean and median values for IB% decline monotonically with the first four recommendation levels, but these values are highest for *strong sell* recommendations (mean = 16.27%; median = 14.9%). Likewise, it is the brokerage firms issuing *strong sell* recommendations that generally derive the highest percentage of their total revenues from commissions. Notably, in each of the five categories, mean COM% is about twice as large as mean IB%. This underscores the importance of trading commissions as a source of revenue for many securities firms. Most recommendations in the sample are at levels 5 (strong buy), 4 or 3. Levels 1 (strong sell) and 2 represent only about 1% and 4% of all recommendations, respectively.

Panel B provides summary statistics on characteristics of individual analysts and their employer firms for our sample of recommendation revisions. The mean (median) share of IB revenue of analyst employers in our sample is about 13.6% (11.2%); the share of brokerage commissions is about 28.7% (24%). On average, an analyst in the sample has about 2.4 years of experience following a given company. Company-specific research experience is highly skewed, however, with median experience of only about 1.2 years.[16] The level of general research experience in I/B/E/S is considerably higher, with a mean of about 6.4 years and a median of about 4.9 years. The mean (median) analyst employer has about 86 (60) analysts working for it. Analysts tend to follow many companies but relatively few industries: during the course of a year, an analyst revises ratings for a mean

[15]Obtained from http://www.nasd.com during October 2004.

[16]One explanation for the short company-specific experience is that the frequency of recommendations experienced large growth in the latter part of our sample period, i.e., the late 1990s and early 2000s. In addition, the annual rate of analyst turnover across brokerage houses is quite high (see, e.g., Hong and Kubik (2003)), and analysts often receive new research coverage assignments after moving to a new firm.

(median) of 17.2 (15) companies and 3 (3) industry groups. Statistics for our analyst reputation variables show that being selected as a top stock picker by *Institutional Investor* or the *Wall Street Journal* is clearly very rare; these honors are received, respectively, only by about 0.5% and 1.8% of all analysts in the sample. It is somewhat more common for an analyst to be selected as a member of the *II* or *WSJ* team: about 3.5% and 13.6% of all recommendation revisions in the sample are made by members of those respective teams.

Finally, Panel C shows that the typical followed company is large, with mean (median) market capitalization of about $8.3 billion ($1.3 billion). Over the time span of a year, a company is tracked by a mean (median) of 9.1 (7) analysts.

4. Conflicts and the levels of analyst recommendations

In this section, we examine whether the levels of stock recommendations are related to the conflicts that analysts face. We start by ascertaining the level of the outstanding recommendation on each stock by each analyst following it at the end of each quarter (March, June, September, December) from 1995 through 2003. An analyst's recommendation on a stock is included only if it is newly issued or was reiterated or revised in the past 12 months.

We estimate an ordered probit model of recommendation levels that enables us to control for other factors, besides conflicts of interest, that may affect the degree of analyst optimism. The main explanatory variables are the percentages of an analyst employer's total revenues that come from investment banking or from brokerage commissions. Following Jegadeesh, et al. (2004) and Madureira (2004), who find that momentum is an important determinant of analyst recommendations, we control for the prior 6-month stock return (RET6).[17] We also control for measures of analyst resources, reputation, experience, workload, and for the size of the followed company. In addition, we control for the consensus of other analysts' recommendations on the stock, which can influence a given analyst's recommendation level. Finally, we control for industry and time period effects by adding dummy variables for I/B/E/S 2-digit S/I/G industries and for each

[17]See also Conrad, et al. (2004) for a detailed analysis of how analysts change their recommendations in response to large stock price moves.

calendar quarter (March 1995, June 1995, etc.). Since recommendation levels take ordered values from 1 (strong sell) to 5 (strong buy), we estimate the following ordered probit model:[18]

(1) $RLEVEL_{ijt} = f(IB\%_{it}, COM\%_{it}, RET6_{jt}, LFIRM_{it}, IITEAM_{it}, WSJTEAM_{it}, CEXP_{it}, NCOS_{it}, CSIZE_{jt}, RECAVG_{jt}$, Industry dummies, Calendar quarter dummies)

where $RLEVEL_{ijt}$ is the level of analyst i's recommendation on stock j at the end of quarter-year t (e.g., March 1995); IB% and COM% are as defined in section 3.2 above; RET6 is the prior 6-month return on the stock; LFIRM is an indicator variable equal to one if the brokerage house is a large firm (i.e., ranks in the top quartile of all houses) in terms of the number of analysts employed in the current calendar year;[19] IITEAM is a binary variable equal to one if an analyst was named in the most recent *Institutional Investor All-American* survey as a First-Team, Second-Team, Third-Team, or Honorable Mention analyst; WSJTEAM is a binary variable that equals one if an analyst was named in the prior *Wall Street Journal* analyst survey as being among the top five stock pickers or earnings forecasters in any industry; CEXP is the number of days an analyst has been producing research (i.e., EPS forecasts, long-term growth forecasts, or stock recommendations) on the company; NCOS is the number of companies in the current year for which an analyst is producing forecasts or recommendations; CSIZE is the natural logarithm of a followed company's market capitalization, measured 12 months before the end of the month; and RECAVG is the mean level of other analysts' contemporaneous recommendations. Z-statistics are based on a robust (Huber/ White/ sandwich) variance estimator.

[18]See Greene (2003) for a detailed exposition of the ordered probit model.

[19]As a measure of resources available to an analyst within a firm, LFIRM is similar in spirit to Clement's (1999) measure of resources, which is defined by whether or not a firm is in the top decile. All of our results are qualitatively similar to those reported here when we replace LFIRM by a binary dummy variable capturing whether or not a firm is in the top decile among all brokerage houses or by the natural logarithm of one plus the number of analysts employed by a firm or by the natural logarithm of a firm's total assets.

Table 2 shows the estimates of two variants of this model. Model 1 excludes the RECAVG variable, while model 2 includes it and omits observations where only one analyst follows the stock. In Panel A, the coefficients of IB% and COM% are both positive, implying that greater conflict with investment banking and brokerage leads an analyst to issue a higher recommendation on a stock. Stocks that experience a price run-up over the prior six months, stocks followed by *Wall Street Journal* All-Star analysts or by busier analysts, stocks of larger companies, and stocks that are highly rated by other analysts, all receive higher recommendations. Analysts employed by larger brokerage houses, *Institutional Investor* All-American analysts, and more experienced analysts all issue lower recommendations. All of these relations are highly statistically significant.

To provide a sense of the magnitude of the main effects of interest, Panel B shows derivatives of the probabilities of each recommendation level with respect to IB% and COM%.[20] For example in model 1, a one standard deviation increase in IB% increases the probability of a buy or strong buy recommendation by (.1082 + .1306) x .1109 = .0265. Compared to the unconditional probability of such recommendations, this is a non-trivial increase of about 4.5% (= .0265 / .595). The effect of a change in COM% is much smaller. A one standard deviation increase in COM% increases the probability of such a recommendation by (.0058 + .007) x .2335 = .003, or about 0.5% (=.003 / .595) of the unconditional probability. Despite possible concerns about loss of reputation, analysts seem to respond to the conflicts they face, particularly those stemming from investment banking.

5. Conflicts and investor response to recommendation revisions

We deal with the stock price response to recommendation revisions in section 5.1 and the response of trading volume in section 5.2.

5.1 Stock price response

This section examines whether an analyst's credibility with investors is related to the degree of conflict that the analyst faces. We interpret the reaction of stock prices to a

[20]Notice that for each explanatory variable, these derivatives sum up to zero across the five recommendation levels.

recommendation revision as an indication of analyst credibility. If conflicts of interest from investment banking and brokerage drive analysts to issue biased and misleading recommendations, then the stock price reaction to such recommendations should reflect the extent to which investors are, on balance, rational or naïve. We focus on revisions in recommendation levels, rather than on recommendation levels *per se*, because revisions are discrete events that are likely to be salient for investors, and previous research finds that revisions have significant information content (see, e.g., Womack (1996) and Jegadeesh, et al. (2004)). To capture the effects of the most commonly observed and economically important types of revisions, we structure our tests around four basic categories: *added to strong buy, added to buy/strong buy, dropped from strong buy, and dropped from buy/strong buy*.[21] We define these four categories to include initiations, resumptions, and discontinuations of coverage because such events may also reflect analysts' positive or negative views about a company. Thus, for example, we consider a stock to be *added to strong buy* under two scenarios: (a) the recommendation level is raised to *strong buy* from a lower level; or (b) coverage is initiated or resumed at the level of *strong buy*. Defining revisions in this fashion yields a sample of 94,892 recommendation revisions made over the 1994-2003 period.

We examine the average stock price response to recommendation revisions in section 5.1.1, conduct univariate tests of the relation between the stock price reaction and measures of analyst conflicts in section 5.1.2, and perform cross-sectional analysis of the stock price reaction in section 5.1.3.

5.1.1. Average stock price response

For stock i that experiences a recommendation revision, we compute the abnormal return over event day t as

(2) $$e_{it} = r_{it} - r_{mt}$$

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[21]Our analysis focuses on these four types of revisions instead of the other four (*added to strong sell,* etc.) because, as shown in Table 1, Panel A, *sell* and *strong sell* recommendations are quite rare. But note that *dropped from buy* and *dropped from buy or strong buy* revisions can entail movement to *sell* or *strong sell* categories.

where r_{it} is the day t stock return (including dividends) for firm i and r_{mt} is the day t stock return on the CRSP equal-weighted market portfolio of NYSE, AMEX and Nasdaq stocks.

The cumulative abnormal return over days t_1 to t_2 is measured as

(3) $$CAR^{i}_{t_1,t_2} = \sum_{t=t_1}^{t_2} e_{it} .$$

Note that the definition of our four recommendation revision groups implies that stocks can be added to a group more than once on a given day. Nonetheless, excluding days on which a stock experiences multiple revisions does not change any of our qualitative results.

Table 3 shows mean and median CARs for three windows around the revision date. The first three columns show the mean and median values of CAR and the sample size, N, for days -1 to 0. The next three columns show corresponding values for days -1 to +1, and the last three columns are for days -5 to +5. The first two rows in the table are for the two groups of upgrades and the last two rows are for downgrades. T-statistics for the difference of mean abnormal returns from zero, computed as in Brown and Warner (1985), are shown in parentheses below the means. P-values for the Wilcoxon test are reported in parentheses below the medians.

It is clear from the table that recommendation revisions have large effects on stock prices. For example, when a stock is added to the strong buy list, it experiences a mean abnormal return of about 2% over the two-day revision period. Downgrades have even larger impacts on stock prices than do upgrades. Strikingly, the two-day mean abnormal return around the *dropped from strong buy* list is -4%. Median values are consistently smaller in magnitude than means, indicating that some revisions lead to very negative price reactions. Mean and median two-day abnormal returns are statistically different from zero for all four groups of forecast revisions. The magnitudes of abnormal returns are slightly larger over the three-day and eleven-day windows than over the two-day window. Overall, these returns are consistent with those found by prior research that examines the stock price impact of recommendation revisions (e.g., Womack (1996) and Jegadeesh, et al. (2004)).

5.1.2. Univariate tests

We next examine whether the stock price impact of recommendation revisions differs according to the degree of analyst conflict. For each type of potential conflict, we divide each group of recommendation revisions into two sub-groups: revisions made by analysts with above-median conflicts and revisions by analysts with below-median conflicts, where medians are calculated across broker-year pairs. Table 4 presents these results. The first two columns in Panel A of the table show the mean three-day CARs for revisions made by analysts whose employers have above-median or below-median IB%. Column 3 shows the absolute value of the t-statistic for the difference between the two means. Columns 4 through 6 present corresponding results for median CARs. The first two rows are for upgrades; the last two rows are for downgrades.

There is no evidence in Panel A to suggest that upgrades made by analysts employed by firms with significant IB business are perceived by the market as being any less credible than upgrades made by other analysts. In fact, the results suggest the opposite. For both upgrades and downgrades, the magnitude of the mean and median stock price reaction to recommendation revisions is significantly greater for the former group of analysts than the latter. However, this finding may reflect the fact that brokerage houses with substantial revenues from IB business tend to be large, prestigious firms that have greater resources and employ high-profile analysts. We control for these factors in multivariate tests in section 5.1.3.

Panel B presents corresponding results for partitions of the sample based on COM%. Here, analyst conflicts seem to undermine credibility. The magnitudes of the mean and median price reactions to recommendation revisions are significantly lower when analysts face more potential brokerage conflicts. This pattern is remarkably consistent: it holds for all four groups of revisions. But these results do not control for other influences on the market reaction, a task that we turn to next.

5.1.3. Cross-sectional analysis

To gain further insight into how investors view analysts' incentives, we estimate cross-sectional regressions of stock price reactions to recommendation revisions over days -1 to +1. The main explanatory variables of interest in these regressions are the magnitudes of conflicts analysts face with their employers' IB and brokerage businesses, which we measure with our IB% and COM% variables. We include variables to control for the size of an analyst's employer, size of the company followed, and the extent of an analyst's reputation, experience and workload. Prior research finds that analysts who have more experience, carry lower workloads or are employed by larger firms tend to generate more precise research (see, e.g., Clement (1999), Jacob, Lys, and Neale (1999), and Mikhail, Walther, and Willis (1997)). In addition, more reputed analysts tend to generate timelier and more accurate research (see, e.g., Stickel (1992), and Hong and Kubik (2003)). Such analysts are likely to be more credible to investors. The empirical model we estimate is:

$$\text{(4)} \quad CAR_i = b_0 + b_1\, IB\%_i + b_2\, COM\%_i + b_3\, LFIRM_i + b_4\, CSIZE_i + b_5\, IITEAM_i + b_6\, WSJTEAM_i + b_7\, CEXP_i + b_8\, NCOS_i + \sum_j b_j\,(\text{Calendar-year dummies}_i) + \sum_k b_k\,(\text{Industry dummies}_{ik}) + e_i,\ i = 1, 2, \ldots, n \text{ recommendation revisions,}$$

where the subscript i denotes a recommendation revision and the explanatory variables are as defined in section 4 above.

We estimate equation (4) separately for each of the four groups of recommendation revisions. The results are shown in Table 5. Each column in the table shows the results of a regression for one group of revisions. The first two regressions are for recommendation upgrades; the last two regressions are for downgrades. T-statistics are reported in parentheses below the coefficient estimates.

As discussed in section 2 above, the rational discounting hypothesis implies that the coefficients of IB% and COM% should be negative for both upgrades and downgrades. In other words, if investors rationally adjust for conflicts of interest, then the greater the conflict an analyst faces, the more investors discount (believe) his recommendation upgrade (downgrade) on a stock. This should lead to lower coefficients on IB% and COM% in both cases. In contrast, naïve investors would follow the recommendations of analysts, ignoring the pressures that analysts face from their employers' other businesses. So the naïve investor hypothesis implies that the coefficients of IB% and COM% should be zero.

The coefficient on IB% is significantly negative for both upgrades and downgrades. The coefficient on COM% is also negative in all four regressions; it is statistically significant in all cases, except in the case of *dropped from strong buy* revisions.[22] Collectively, these results favor the rational discounting hypothesis over the naïve investor hypothesis. The magnitudes of these effects are non-trivial. For instance, a one standard deviation increase in IB% leads to a change of about -0.3% (-0.42%) in the three-day abnormal return around the move to (from) a *strong buy* recommendation. Similarly, a one standard deviation increase in COM% leads to a change of about -0.38% (-0.22%) in the corresponding abnormal return around the move to (from) a *buy or strong buy* recommendation.

The results for control variables are also noteworthy. The dummy variable for a large analyst employer is positively related to the market reaction to upgrades and negatively related to the reaction to downgrades. This finding is consistent with the idea that revisions by analysts employed by larger brokerage houses are more credible to investors. Size of the company followed is negatively related to the market reaction to upgrades, consistent with the notion that performance is more difficult to forecast for larger companies. Revisions by *Institutional Investor All-American* analysts are positively related to the stock price reaction to upgrades and negatively related to the reaction to downgrades, suggesting that *All-American* analysts are viewed as being more credible. This is a notable finding; we are unaware of previous work documenting a relationship between analyst reputation and the stock price reaction to recommendation revisions. As the coefficient on WSJTEAM[23] indicates, however, being designated as a *Wall Street Journal All-Star* does not seem to enhance the credibility of an analyst's recommendations. The lack of an effect here may be somewhat surprising given that the *WSJ* has a much broader readership base than *Institutional Investor* magazine. One explanation is that *II* analyst rankings are based on an opinion poll of money managers, who control substantial assets and therefore directly affect stock prices, while *WSJ*

[22]These and all subsequent regression results in the paper are qualitatively similar when we winsorize the dependent variable at the first and 99th percentiles of its distribution.

[23]Although IITEAM and WSJTEAM both measure aspects of analyst reputation, they are not highly correlated. The correlation coefficient is 0.14 across all upgrades and 0.13 across all downgrades.

rankings are based on strictly quantitative measures of analysts' past stock-picking or forecasting performance. The market reactions to upgrades as well as downgrades are positively related to analyst experience. This finding suggests that an analyst who has been following a company over a longer period of time is less susceptible to investment banking pressures. Finally, analyst workload is negatively (positively) related to the reaction to upgrades (downgrades), consistent with the view that busier analysts' opinions tend to get discounted by the market. All these relations are statistically significant.

5.2. Response of trading volume

This section complements the evidence from section 5.1. We address the same basic question as in the earlier sub-section: Is an analyst's credibility related to the degree of conflict that he faces? But now we measure analyst credibility via changes in the volume of trade around recommendation revisions.[24] Revisions of analyst recommendations can affect trading volume by inducing investors to rebalance their portfolios to reflect updated beliefs. We examine the average trading volume response to recommendation revisions in section 5.2.1 and conduct univariate tests of the relation between abnormal volume and measures of analyst conflicts in section 5.2.2. Section 5.2.3 contains a cross-sectional analysis explaining abnormal volume.

5.2.1. Average response of trading volume

We compute the abnormal volume for a trading day t as the mean-adjusted share turnover for stock i:[25]

(5) $e_{it} = v_{it} - v_i$,

where v_{it} = mean daily trading volume of stock i over day t divided by common shares outstanding on day t, and v_i = mean of v_{it} over days -35 to -6.

The cumulative abnormal volume for firm i over days t_1 to t_2 is measured as

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[24]Many prior studies have used trading volume to examine investors' response to informational events (see, e.g., Shleifer (1986), Jain (1988), Jarrell and Poulsen (1989), Meulbroek (1992), and Sanders and Zdanowicz (1992)).

[25]This approach has been used by a number of prior studies (e.g., Shleifer (1986), Vijh (1994), and Michaely and Vila (1996)).

$$\text{(6)} \qquad \mathrm{CAV}^{i}_{t_1, t_2} = \sum_{t=t_1}^{t_2} e_{it}.$$

Table 6 shows mean and median values of CAV over three windows surrounding revisions in analyst stock recommendations. Over the two-day revision period, the mean abnormal volume is positive for both upgrades and downgrades, but its magnitude is substantially larger for downgrades. The move to (from) the strong buy list increases a stock's trading volume by a mean of about 0.9% (2.6%) of the outstanding shares, compared to a normal day's volume. For longer windows, mean abnormal volumes are substantially higher for downgrades. Median values are lower than the means. Each mean and median abnormal volume is statistically greater than zero, with a p-value below .01. Clearly, revisions of stock recommendations by analysts generate trading activity.

5.2.2. Univariate tests

As a first step in understanding investors' volume response, we examine whether abnormal trading volume around revision events differs according to the degree of conflict faced by analysts. Table 7 shows, in a format similar to that of Table 4, mean and median values of CAV over days -1 to +1 for analysts with different degrees of conflict. Panel A focuses on IB conflicts and Panel B on brokerage conflicts. For upgrades in Panel A, the mean CAV for analysts with greater IB conflicts is similar to that for less conflicted analysts for the *added to buy or strong buy* group; it is slightly higher for analysts with greater conflicts for the *added to strong buy* group. For downgrades, the mean CAV is significantly higher for more conflicted analysts in both groups of revisions. Median CAV is significantly higher for more conflicted analysts in all four groups of revisions. Recommendation revisions of analysts employed by firms with more IB business generate significantly greater abnormal trading volume.

The picture is quite different in Panel B. Here, mean abnormal volume around downgrades is significantly lower for more conflicted analysts. For upgrades, there is no significant difference between the two groups of analysts. Median abnormal volume is statistically lower for more conflicted analysts for both upgrades and downgrades. These tests do not control for other economic determinants of abnormal volume, a task that we turn to next.

5.2.3. Cross-sectional analysis

We next estimate cross-sectional OLS regressions of cumulative abnormal volume over days -1 to +1 surrounding the recommendation revisions. The explanatory variables in the regressions are the same as in equation (4) above. The results are shown in Table 8. The main explanatory variables of interest in these regressions are our measures of IB and brokerage conflicts, IB% and COM%. Based on the discussion in section 2, the rational discounting hypothesis implies that the coefficients of IB% and COM% should be negative for upgrades and positive for downgrades. The naïve investor hypothesis implies that both coefficients should be zero for both types of revisions.

Table 8 provides strong support for the rational discounting hypothesis. The coefficients of both IB% and COM% variables are significantly negative for both groups of upgrades, and they are generally significantly positive for both groups of downgrades. The magnitudes of these effects are non-trivial. A one standard deviation increase in IB% results in a change in the three-day abnormal volume around the addition (omission) of a stock to (from) the strong buy list of about -0.12% (+0.36%) of the outstanding shares. A corresponding change in COM% results in a change in abnormal volume of about -0.15% (+0.14%).

Recommendation revisions by larger brokerage houses generate more trading. Abnormal volume is also larger for revisions involving smaller companies. Revisions by *II All-American* team members generate significantly more abnormal volume for the *dropped from buy or strong buy* group. Upgrades (downgrades) by more experienced analysts result in larger (smaller) abnormal volume. Upgrades by analysts who carry heavier workloads are less credible.

6. Conflicts and the performance of recommendation revisions

In this section, we examine the investment performance of analysts' recommendation revisions. We follow the performance of stocks that experience each type of recommendation revision (e.g., *added to strong buy*) for up to 12 months[26]

[26] We restrict the performance horizon to twelve months to exclude stale recommendations from the analysis.

following the month of revision or for the length of time that the revised recommendation remains in force, whichever is smaller. Under the assumption of market efficiency, these post-recommendation returns measure the performance of a revised recommendation. Notice that there is information conveyed by the fact that a newly revised recommendation remains in force over a period of time because the analyst is free to change the recommendation at any time.

Unlike in section 5.1, where we compute abnormal returns over a few days around a recommendation revision on a stock, we are now interested in measuring abnormal performance over periods of up to 12 months. So the benchmark used to compute abnormal returns is somewhat more important than in section 5.1. But since we are interested in measuring abnormal performance over the medium-term (3 to 12 months), the results here are likely to be less sensitive to the benchmark employed than in studies of long-run stock performance, where the time period of interest can be as long as 5 to 10 years (see, e.g., Agrawal, Jaffe and Mandelker (1992), and Agrawal and Jaffe (2003)).

We analyze the average performance of recommendation revisions in section 6.1, the performance of revisions by analysts with different degrees of conflicts in section 6.2, and the cross-section of performance in section 6.3.

6.1 Average performance

We use the calendar-time portfolio regression approach of Jaffe (1974) and Mandelker (1974). As Fama (1998) points out, this approach avoids the problem of cross-correlation in residuals across stocks in a given calendar month. In addition, we combine the Fama and French (1993) 3-factor model with the regression across time and securities (RATS) approach of Ibbotson (1974). The approach is quite parsimonious in its data requirement and consequently avoids problems caused by survival bias.

To evaluate the performance of a group of stocks over months +1 to +12 following the month of their inclusion (month 0) in a group of revisions (such as *added to strong buy* list), we start by estimating the following cross-sectional regression by OLS for month +1:

(7) $R_p - R_{fp} = \alpha + \beta_1 (R_{mp} - R_{fp}) + \beta_2 SMB_p + \beta_3 HML_p + \varepsilon_p,$

where p denotes a calendar month over the sample period, R_p is the return over month +1 for an equal-weighted portfolio of all unique stocks that experienced the revision in calendar month p (e.g., January 1994);[27] R_{fp} is the corresponding monthly return on the risk-free asset; SMB equals the monthly return on a portfolio of small firms minus the return on a portfolio of big firms; and HML is the monthly return on a portfolio of high book-to-market ratio firms minus the return on a portfolio of low book-to-market ratio firms.

The unit of observation in the regression is a portfolio corresponding to a calendar month. For example, for our sample period of January 1994 to December 2003, p=1 may correspond to an equal-weighted portfolio of all stocks that are added to the group in January 1994. The sample size, n, in the regression is up to 120 calendar month portfolios. The time series of monthly returns on R_f, SMB and HML are obtained from Ken French's website.[28] The coefficient estimate of α from equation (7) measures the abnormal monthly performance of stocks in the group. We denote this estimate as $\hat{\alpha}_1$ and its associated t-statistic as $t(\hat{\alpha}_1)$. We define the average abnormal return (AAR) for month +1 as

(8) $AAR_1 = \hat{\alpha}_1,$

(9) $t(\hat{\alpha}_1) = \hat{\alpha}_1 / s_1,$

where s_1 is the standard error of $\hat{\alpha}_1$.

We next repeat this procedure for months +2, +3, …, +12 to obtain a time series of $\hat{\alpha}_i$, i = 1, 2, …, 12, and their associated t-statistics. We then compute the cumulative average abnormal return (CAAR) over months +1 to +12 and its associated t-statistic as follows:

[27]We ignore the fact that a stock's rating may be upgraded (or downgraded) by more than one analyst in a given calendar month.

[28]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html (accessed in November 2004).

(10) $\text{CAAR}_{+1,\,+12} = \sum_{i=1}^{12} AAR_i$

(11) $s(\text{CAAR}_{+1,\,+12}) = [\sum_{i=1}^{12} s_i^2]^{1/2}$, assuming that $\hat{\alpha}_i$'s are independent, and

(12) $t(\text{CAAR}_{+1,\,+12}) = \text{CAAR}_{+1,\,+12} / s(\text{CAAR}_{+1,\,+12})$

We compute CAARs over other intervals similarly.

Table 9 shows the performance of analysts' recommendation revisions. The first three columns show the CAAR, its t-statistic, and sample size (N) for month 0 (the month of a revision). The next three sets of three columns each show corresponding values for months +1 to +3, +1 to +6, and +1 to +12. N denotes the average number of calendar-month portfolios used in regressions for each event month in a window. The first two rows are for portfolios of upgrades; the next two rows are for downgrades.

The main focus in Table 9 is on medium-term performance. Over the period of three months following the month of recommendation revision, the average abnormal returns to upgrades are positive and the returns to downgrades are negative. The magnitudes of these returns are non-trivial, although they are not as large as the returns for the month of revision. For example, the addition (removal) of a stock to (from) the strong buy list has a CAAR of about 1.5% (-2%). CAARs are statistically different from zero for all four groups of revisions.

Over months +1 to +6, the magnitudes of the CAARs are somewhat bigger, particularly for downgrades. For example, the addition to (removal from) the strong buy list has a CAAR of about 1.8% (-4%). Once again, the CAARs here are statistically significant in all four groups. Over months +1 to +12, the statistical significance of abnormal returns vanishes for upgrades, but remains quite strong for downgrades. The magnitude of the latter abnormal return is quite large. For example, a stock that is dropped from the strong buy list has a sizeable average abnormal return of about -6.8%. This return is highly statistically significant.

For the month of revision (month 0), abnormal returns are quite large in magnitude and are statistically significant for all four groups. They are positive for upgrades and negative for downgrades. For example, the addition (removal) of a stock to (from) the strong buy list results in an average abnormal return of about 3.3% (-5%).

These results are similar to those reported in Table 3 for the 11-day window around the revision date.

6.2 Univariate tests

We next examine whether the medium-term performance of analysts' recommendation revisions differs according to the degree of analysts' IB and brokerage conflicts. We start by constructing an equal-weighted portfolio consisting of all stocks that experience a particular type of recommendation revision by a group of analysts (e.g., *added to strong buy* by analysts with above-median IB%) in each calendar month in the sample. A stock remains in a portfolio until the end of the window of interest or until the recommendation is changed again, whichever is earlier. We then estimate equation (7) above by cross-sectional OLS regression for month +1. We repeat this procedure for subsequent months and compute CAARs as in section 6.1.

The first two columns in Panel A of Table 10 show CAARs for months +1 to +3 for revisions by analysts who work for firms with above-median IB% and by other analysts. Column 3 reports the absolute value of the t-statistic for the difference between the two groups. The next three columns show corresponding values for CAARs over months +1 to +6. The last three columns are for months +1 to +12. The first two rows are for the two groups of upgrades and the next two rows are for downgrades.

Panel A shows no significant difference in the performance of recommendation revisions between the two groups of analysts. This is true regardless of whether performance is measured over three, six, or twelve months. The results are similar in Panel B, where we partition analysts based on the magnitude of brokerage conflicts they face.

6.3 Cross-sectional analysis

Finally, we perform cross-sectional regressions of medium-term performance of analysts' recommendation revisions. We estimate an equation similar to equation (4) above, except that the dependent variable here is the cumulative abnormal return (CAR) for a firm over months +1 to +12 following a recommendation revision. We compute this CAR by estimating a time-series analog of regression equation (7) above over months +1 to +12 for each stock in our sample of recommendation revisions. The intercept from this regression is our estimate of the medium-term performance of the recommendation revision. The explanatory variables in the cross-sectional regressions of CAR are the same as in equation (4). Observations involving a stock that occur within 12 months of an earlier revision are omitted from each regression.[29] The results are presented in Table 11 in a format similar to that of Table 5.

As discussed in section 2, the rational discounting hypothesis says that investors properly take into account the conflicts of interest that analysts face upfront. This implies that the magnitudes of those conflicts should be unrelated to the subsequent performance of their recommendations. Therefore the coefficients of IB% and COM% variables in the Table 11 regressions should be zero. The naïve investor hypothesis says that investors ignore the conflict of interest and pay for their naïveté later on. This implies that the coefficients of IB% and COM% variables should be negative. In regressions for each of the four groups of recommendation revisions in Table 11, the coefficients of these variables are essentially zero. These results favor the rational discounting hypothesis. The performance of recommendation upgrades is negatively related to company size and analyst workload; it is positively related to an analyst's company-specific research experience. None of the other variables is statistically significant.

7. Bubble vs. post-bubble periods

Our findings in section 4 suggest that analysts succumb to the conflicts they face, particularly with investment banking, by inflating their stock recommendations. However, the results in sections 5.1.3, 5.2.3 and 6.3 strongly support the rational discounting hypothesis. Investors apparently take upgrades by more conflicted analysts with a grain of salt; but when conflicted analysts issue a downgrade, investors take the recommendation seriously. This behavior results in lower abnormal returns and lower trading volume response to upgrades by more conflicted analysts. And it results in lower abnormal returns and higher trading volume response to their downgrades. Also, in line with the rational discounting hypothesis, we find no relation between the degree of analyst conflict and the 12-month investment performance of revised recommendations.

[29]The results are qualitatively similar when we include these observations.

We next exploit the fact that our sample spans both the late 1990s U.S. stock bubble and a post-bubble period. During the bubble period, IPO and merger activities and stock prices were near record highs, and media attention was focused on analysts' pronouncements. We therefore examine whether analyst behavior and investor response to analyst recommendations differ during the bubble and post-bubble periods. Given the euphoria on Wall Street and among investors during the bubble, analysts may have been under acute pressure to generate investment banking fees and brokerage commissions. As for investors, they may have discounted analyst opinions more during this period in response to heightened conflicts; or they may have been swept by euphoria and consequently behaved naïvely, as casual empiricism and numerous stories in the media suggest.

We estimate regressions similar to those in Table 2 for recommendation levels, Table 5 for announcement abnormal returns, Table 8 for announcement abnormal volume, and Table 11 for investment performance of revisions, except that we now replace the IB% and COM% variables by four variables: IB%*BUBBLE, IB%*POST, COM%*BUBBLE and COM%*POST. The variable BUBBLE equals 1 for revisions made between January 1996 and March 2000; it equals 0 otherwise. The variable POST equals 1 for revisions made between April 2000 and December 2003; it equals 0 otherwise. For regressions corresponding to Table 2, we also replace the calendar-quarter dummies with a post-regulation indicator (equal to 1 for quarters ending after May 2002). In May 2002, both the NYSE and NASD considerably tightened the regulations on the production and dissemination of sell-side analyst research.[30] These regulations may have exerted a downward pressure on recommendation levels, as the findings of Barber, et al. (2003) and Madureira (2004) suggest. The results of these regressions are presented in Table 12. To save space, we only report the coefficient estimates of IB% and COM%.

Panel A shows that analysts appear to have inflated their recommendations in response to investment banking conflicts during both the bubble and post-bubble periods. But the magnitude of this effect is substantially greater during the bubble period than post-bubble. This difference is statistically significant. The magnitude of the effect is

[30]See NYSE Amended Rule 472, 'Communications with the Public,' and NASD Rule 2711, 'Research Analysts and Research Reports.'

smaller for brokerage conflicts than for IB conflicts during both periods. In fact, the effect for brokerage conflicts is negative during the bubble; it is positive and significantly higher post-bubble.

Panel B shows the results for regressions of three-day abnormal stock returns, three-day abnormal volume, and 12-month stock performance. The first two columns in the panel show the coefficients for the bubble and post-bubble periods, respectively, for the *added to strong buy* group. Column 3 shows the p-value for the difference between the two coefficients. The next three sets of three columns each show corresponding results for the *added to buy or strong buy*, *dropped from buy or strong buy*, and *dropped from strong buy* groups.

In regressions of three-day abnormal returns, the coefficients of both IB% and COM% are significantly negative during the bubble period for both groups of upgrades; for IB%, they are significantly lower during the bubble period than post-bubble. For downgrades, while the coefficients of both IB% and COM% are generally negative in both periods, the difference between the two periods is statistically insignificant at the 5% level.

In regressions of three-day abnormal volume, the coefficients of IB% and COM% are generally significantly negative during the bubble period for both groups of upgrades. Both coefficients are lower during the bubble period than post-bubble, and the difference is statistically significant for COM% for the added to buy or strong buy list. For downgrades, the coefficients of both IB% and COM% are always positive and generally statistically significant, particularly during the bubble period; the coefficient of IB% is significantly higher during the bubble period than post-bubble.

The results for regressions of 12-month stock performance for each sub-period generally mirror those for the full sample. Here, the coefficients of both IB% and COM% are almost always statistically insignificant for all four groups of revisions in each sub-period. The differences in these coefficients are statistically insignificant between the two sub-periods in all eight cases.

Overall, this evidence further supports the rational discounting hypothesis over the naïve investor hypothesis. Investors appear to have been attuned to analysts' potential conflicts in both the bubble era and the post-bubble era. There is no evidence to suggest that investors ignored conflicts during the bubble years; if anything, they seem to have discounted investment banking conflicts more during the bubble.

8. Summary and conclusions

Following the collapse of the late-1990s U.S. stock market bubble, there has been a widespread hue and cry from investors and regulators over the conflicts of interest faced by Wall Street stock analysts. The discovery of e-mails, in which analysts were privately disparaging stocks that they were touting publicly, led to the landmark $1.4 billion settlement between ten leading Wall Street firms and securities regulators in April 2003. The settlement requires the firms to disclose investment banking conflicts in analyst reports and imposes a variety of restrictions designed to strengthen the Chinese Walls that separate research from investment banking. Part of the settlement funds are set aside for investor education and for research produced by independent firms. The settlement basically presumes that analysts respond to the conflicts by inflating their stock recommendations, and that investors take analyst recommendations at face value.

This paper examines the extent to which analysts respond to the conflicts they face by inflating their stock recommendations, and the extent to which investors discount analyst recommendations in accordance with such conflicts. We employ a unique, hand-collected dataset that contains the annual revenue breakdown of analyst employers into revenues from IB, brokerage and other businesses. We use this information to construct quantitative measures of the importance of these businesses to analyst employers. Our approach takes into account pressures from both existing and potential IB clients as well as from brokerage business. We attempt to distinguish between two competing hypotheses about investors' response to these conflicts: the rational discounting hypothesis and the naïve investor hypothesis.

We address four issues. First, is the level of stock recommendations (strong buy, buy, hold, sell, and strong sell) related to the relative importance of IB and brokerage businesses to analysts' employers? Second, to what extent do investors discount the opinions of analysts who face greater degrees of conflict? Specifically, are the stock price and volume reactions to recommendation revisions systematically related to the magnitude of potential IB or brokerage conflicts? Third, is the medium-term (3 to 12-

month) performance of analysts' recommendation revisions related to the magnitude of potential conflicts? Finally, do the analyst response to conflicts and the investor response to analyst recommendations differ between the late 1990s stock bubble versus the post-bubble period? We address these questions using univariate tests as well as multivariate regressions that control for characteristics of individual analysts, their employers, and the companies they cover.

Consistent with the view of the media and regulators, we find that optimism in stock recommendations is positively related to the importance of IB business to an analyst's employer. This pattern is more pronounced during the late 1990s stock market bubble with respect to IB conflict. However, we provide several pieces of empirical evidence that suggest that investors are sophisticated enough to adjust for this bias. First, the reactions of both stock prices and trading volumes to recommendation upgrades exhibit significant negative relations with the magnitude of potential IB or brokerage conflicts faced by analysts. For instance, over the three days surrounding upgrades to *strong buy*, a one standard deviation increase in the proportion of revenue from investment banking (brokerage commissions) is associated with a 0.3% (0.38%) decrease in abnormal return and a 0.12% (0.15%) decrease in abnormal volume. These results suggest that investors assign lower credibility to an analyst's upgrade when the analyst is subject to greater pressures to issue an optimistic view. For downgrades, the corresponding relations are negative for stock prices and positive for trading volume. This pattern is consistent with the idea that investors perceive an analyst to be more credible if he is willing to voice an unfavorable opinion on a stock despite greater pressures to be optimistic.

Second, we find no evidence that the one-year investment performance of recommendation revisions is related to the magnitude of analyst conflicts, either for upgrades or for downgrades. This finding suggests that on average, investors properly discount analyst opinions for potential conflicts at the time the opinion is issued. Finally, investors appear to have discounted analyst opinions more during the late 1990s stock bubble. This evidence does not support the popular view that recommendations of sell-side analysts led investors to throw caution to the wind during the bubble period.

Overall, our empirical findings suggest that while analysts respond to investment banking and brokerage conflicts by inflating their stock recommendations, the market discounts analyst opinions after taking their conflicts into account. These findings are reminiscent of the story of the nail soup in Brealey and Myers (1991), except that here, analysts (rather than accountants) are the ones who put the nail in the soup and investors (rather than analysts) are the ones to take it out. Our finding that the market is not fooled by biases stemming from conflicts of interest echoes similar findings in the literature on conflicts of interest in universal banking (e.g., Kroszner and Rajan (1994) and Gompers and Lerner (1999)) and on bias in financial media (e.g., Bhattacharya, et al. (2004) and Reuter and Zitzewitz (2004)). Finally, our findings do not support the notion that investors were systematically misled over the last decade by analyst recommendations and call into question the need for aggressive regulation of analyst research.

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Table 1

Characteristics of Analysts, Analyst Employers, and Companies Followed

The table shows statistics on characteristics of analysts, analyst employers, and followed companies for 110,493 stock recommendations (including 94,892 recommendation revisions) drawn from the I/B/E/S U.S. Detail Recommendations History file from 1994-2003. Recommendation revisions include recommendation changes as well as initiations, resumptions, and discontinuations of coverage. Panel A reports, by recommendation levels, the percentages of analyst employer revenue that come from investment banking (IB%) or brokerage commissions (COM%). Panel B shows characteristics of analysts and analyst employers for the sample of recommendation revisions. Analyst experience is measured from all analyst research activity in I/B/E/S, including EPS forecasts, long-term earnings growth forecasts, and stock recommendations. An analyst is considered to be a top stock picker or team member if he appeared in the relevant portion of the most recent analyst survey by *Institutional Investor* or *Wall Street Journal* at the time of a recommendation revision. Panel C shows the size (i.e., market capitalization 12 months before the end of the current month) and analyst following (i.e., stock recommendation coverage) of companies experiencing recommendation revisions.

Panel A: Revenue Sources of Analyst Employer by Recommendation Level

Recommendation Level	IB % Mean	IB % Median	COM % Mean	COM % Median	Sample Size
5 (Strong Buy)	13.94	11.81	29.87	24.09	28,901
4 (Buy)	13.81	11.21	26.68	17.22	37,478
3 (Hold)	12.68	11.13	28.44	24.07	37,883
2 (Sell)	11.61	10.55	23.13	16.12	4,875
1 (Strong Sell)	16.27	14.90	33.44	24.95	1,356
P-value for (4&5) vs. (1&2)	0.0000	0.0000	0.0000	0.0023	

Panel B: Analyst and Firm Characteristics for Sample of Recommendation Revisions

	Mean	Median	Std. deviation	Sample Size
IB %	13.60	11.25	11.93	94,892
COM %	28.74	24.07	24.75	94,892
Analyst's company-specific experience (years)	2.42	1.20	3.29	85,531
Analyst's general experience (years)	6.41	4.90	5.32	85,531
Number of analysts employed by a firm	86.34	60	79.73	94,618
Number of companies covered by an analyst	17.24	15	12.93	84,016

Table 1 (cont.)

		Mean	Median	Std. Deviation	Sample size
Number of 4-digit I/B/E/S S/I/G industry groups covered by an analyst		3.05	3	1.90	84,014
Institutional Investor All-American Stock Picker		0.005	0	0.07	85,531
Institutional Investor All-American Team Member		0.035	0	0.18	85,531
Wall Street Journal All-Star Stock Picker		0.018	0	0.13	85,531
Wall Street Journal All-Star Team Member		0.136	0	0.34	85,531
Panel C: Characteristics of Companies Experiencing Stock Recommendation Revisions					
		Mean	Median	Std. Deviation	Sample size
Market Capitalization ($ millions)		8,277.88	1,263.41	26,527.55	81,333
Analyst Following		9.14	7	6.88	92,869

Table 2

Ordered Probit Analysis of Recommendation Levels

The table shows the results of ordered probit regressions explaining individual analysts' stock recommendation levels at the end of each quarter (March, June, September, December) from 1995 through 2003. Observations are excluded if the analyst issued no new or revised recommendation in the past 12 months. IB% (COM%) is the percentage of total revenues derived from investment banking (brokerage commissions). LFIRM is an indicator variable that equals one if a brokerage house is a large firm (i.e., in the top quartile of all houses) based on the number of analysts issuing stock recommendations on I/B/E/S in a given calendar year. IITEAM (WSJTEAM) is an indicator variable that equals one if the recommending analyst was listed as an All-American (All-Star) in the most recent *Institutional Investor* (*Wall Street Journal*) analyst ranking. CEXP is the number of days that an analyst has been issuing research on I/B/E/S (including any forecasts or recommendations) on a company. NCOS equals the number of companies followed by an analyst in the current calendar year. CSIZE is the natural logarithm of a followed company's market capitalization, measured twelve months prior to the end of the current month. RET6 is the prior 6-month return on the stock. RECAVG is the mean level of all other analysts' contemporaneous recommendations on the stock. The regression includes dummy variables for 2-digit I/B/E/S S/I/G industries and for calendar-quarters. Test statistics are based on a robust variance estimator.

Panel A: Coefficient Estimates

	Model 1			Model 2		
Explanatory Variable	Coeff.	Z-statistic	s.d.	Coeff.	Z-statistic	s.d.
IB%	0.6115	28.09	0.1109	0.6292	24.77	0.1051
COM%	0.0327	2.84	0.2335	0.0418	2.09	0.2323
RET6	0.0330	3.53	1.0225	0.0322	3.33	0.9815
LFIRM	-0.1359	-19.38	0.3898	-0.1102	-12.56	0.3775
IITEAM	-0.0547	-2.81	0.0983	-0.0399	-2.43	0.1024
WSJTEAM	0.0185	2.23	0.2631	0.0209	1.04	0.2643
CEXP	-0.00005	-30.73	1430.79	-0.00004	-19.91	1472.09
NCOS	0.00005	16.84	818.62	0.00005	15.41	813.03
CSIZE	0.0575	44.86	1.9376	0.0135	8.44	1.8430
RECAVG				0.2831	69.74	0.6778
Number of observations	255,261			213,011		
p-value, chi-squared test	< 0.0001			< 0.0001		

Panel B: Marginal Effects and Sample Distribution

		Strong Sell	Sell	Hold	Buy	Strong Buy
Model 1	IB%	-0.0309	-0.0723	-0.1356	0.1082	0.1306
	COM%	-0.0017	-0.0039	-0.0073	0.0058	0.0069
	Observed Frequency	.010	.039	.356	.330	.265
Model 2	IB%	-0.0536	-0.0954	-0.0669	0.1290	0.0869
	COM%	-0.0023	-0.0029	-0.0029	0.0056	0.0037
	Observed Frequency	.010	.040	.360	.326	.264

Table 3

Abnormal Returns Surrounding Revisions in Analyst Stock Recommendations

The table reports mean and median values of cumulative abnormal stock returns (CARs) surrounding recommendation revisions (i.e., recommendation changes and initiations, resumptions, and discontinuations in coverage). Subscripts indicate the days relative to the revision date (day 0) over which a CAR is measured. The sample of revisions is obtained from the I/B/E/S U.S. Detail Recommendations History file over the period 1994-2003. Recommendation revisions are classified according to the level of any existing recommendation and whether coverage is being initiated or dropped. For example, a revision by an analyst is classified as *added to strong buy* if the new recommendation is *strong buy* and either (a) the previous recommendation was lower than *strong buy*; or (b) analyst coverage by the brokerage house is resumed or initiated. A recommendation is classified as *dropped from strong buy* if the previous recommendation was *strong buy* and either (a) the new recommendation is lower than *strong buy*; or (b) research coverage on the company is stopped. T-statistics (in parentheses below mean abnormal returns) for the difference from zero are computed as in Brown and Warner (1985). P-values (in parentheses below medians) for the difference from zero are from a Wilcoxon test. N denotes sample size.

		$CAR_{-1,0}$				$CAR_{-1,+1}$				$CAR_{-5,+5}$		
Recommendation Revision		Mean (t-stat)	Median (p-value)	*N*		Mean (t-stat)	Median (p-value)	*N*		Mean (t-stat)	Median (p-value)	*N*
Upgrades												
Added to Strong Buy		0.0207 (49.53)[a]	0.0109 (0.000)	24,560		0.0240 (46.89)[a]	0.0130 (0.000)	24,556		0.0263 (26.84)[a]	0.0187 (0.000)	24,499
Added to Buy/ Strong Buy		0.0149 (46.47)[a]	0.0071 (0.000)	36,879		0.0165 (42.01)[a]	0.0085 (0.000)	36,875		0.0207 (27.53)[a]	0.0128 (0.000)	36,780
Downgrades												
Dropped from Buy/Strong Buy		-0.0337 (-56.21)[a]	-0.0126 (0.000)	33,322		-0.0358 (-48.75)[a]	-0.0155 (0.000)	33,262		-0.0491 (-34.92)[a]	-0.0287 (0.000)	33,197
Dropped from Strong Buy		-0.0399 (-49.88)[a]	-0.0153 (0.000)	22,825		-0.0427 (-43.58)[a]	-0.0183 (0.000)	22,795		-0.0570 (-30.38)[a]	-0.0326 (0.000)	22,767

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

Table 4
Abnormal Returns over Days -1 to +1 Surrounding Revisions in Stock Recommendations by Analysts with Differing Degrees of Potential Conflict

The table shows mean and median CARs for eight groups of recommendation revisions. CARs within each group are reported separately for analysts whose employers derive above or below median percentage of revenue from investment banking (Panel A) or brokerage commissions (Panel B). The sample of recommendation revisions is obtained from the I/B/E/S U.S. Detail Recommendations History file for the period 1994-2003. Revisions are defined and classified as in Table 3. Investment banking revenue and commission revenue are measured at the end of the latest fiscal year preceding a recommendation revision. Median values for investment banking and commission revenue fractions are computed across all firm-year observations in the sample. T-statistics for tests for differences in means and p-values from nonparametric Wilcoxon tests for differences in distributions are also reported.

Panel A: Investment Banking Revenue

	Mean CAR			Median CAR			Number of Obs.	
Recommendation Revision	IB% above median	IB% below median	|t-stat.|	IB% above median	IB% below median	p-value	IB% above median	IB% below median
Upgrades								
Added to Strong Buy	0.0266	0.0169	7.78[a]	0.0158	0.0072	0.0000	16,835	7,093
Added to Buy/ Strong Buy	0.0180	0.0122	5.93[a]	0.0099	0.0048	0.0000	25,747	10,254
Downgrades								
Dropped from Buy/Strong Buy	-0.0404	-0.0237	10.78[a]	-0.0177	-0.0101	0.0000	23,070	9,406
Dropped from Strong Buy	-0.0478	-0.0291	9.76[a]	-0.0209	-0.0119	0.0000	15,752	6,502

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

Table 4 (cont.)

Panel B: Brokerage Commission Revenue												
		Mean CAR				Median CAR				Number of Obs.	
Recommendation Revision		COM% above median	COM% below median	|t-stat.|		COM% above median	COM% below median	p-value		COM% above median	COM% below median
Upgrades											
Added to Strong Buy		0.0157	0.0261	7.69[a]		0.0063	0.0152	0.0000		5,425	18,503
Added to Buy/ Strong Buy		0.0092	0.0182	8.20[a]		0.0032	0.0097	0.0000		7,412	28,589
Downgrades											
Dropped from Buy/Strong Buy		-0.0254	-0.0382	7.31[a]		-0.0108	-0.0165	0.0000		6,604	25,872
Dropped from Strong Buy		-0.0288	-0.0463	8.45[a]		-0.0115	-0.0203	0.0000		5,072	17,182

Table 5
Cross-sectional Regressions of Abnormal Returns Surrounding Recommendation Revisions

Each column in the table shows the results of a cross-sectional OLS regression explaining cumulative abnormal stock returns over days -1 to +1 surrounding a particular type of recommendation revision. Revisions are defined and classified as in Table 3. IB% (COM%) is the percentage of total revenues derived from investment banking (brokerage commissions). LFIRM is an indicator variable equal to one if a brokerage house is a large firm (i.e., in the top quartile of all houses) as measured by the number of analysts issuing I/B/E/S stock recommendations in a given calendar year. CSIZE is the natural logarithm of a followed company's market capitalization, measured 12 months prior to the end of the current month. IITEAM (WSJTEAM) is an indicator variable equal to one if the recommending analyst was listed as an All-American (All-Star) in the most recent *Institutional Investor* (*Wall Street Journal*) annual analyst survey. CEXP is the number of days that an analyst has been issuing research on I/B/E/S (including any forecasts or recommendations) on a company. NCOS equals the number of companies followed by an analyst in the current calendar year. T-statistics are reported in parentheses below coefficient estimates. All regressions include calendar-year and 2-digit I/B/E/S S/I/G industry dummies (not reported).

Explanatory Variable	Added to Strong Buy	Added to Buy/ Strong Buy	Dropped from Buy /Strong Buy	Dropped from Strong Buy
Intercept	0.0331 (0.40)	0.0362 (0.45)	-0.204 (-1.63)	-0.2094 (-1.65)
IB%	-0.0261 (-5.01)[a]	-0.0142 (-3.30)[a]	-0.0195 (-2.70)[a]	-0.0353 (-3.94)[a]
COM%	-0.0191 (-6.83)[a]	-0.0153 (-6.57)[a]	-0.0090 (-2.44)[b]	-0.0014 (-0.32)
LFIRM	0.0116 (7.39)[a]	0.0089 (6.85)[a]	-0.0243 (-11.90)[a]	-0.0219 (-9.18)[a]
CSIZE	-0.0054 (-15.85)[a]	-0.0039 (-14.20)[a]	-0.0007 (-1.54)	0.0014 (2.71)[a]
IITEAM	0.0160 (4.22)[a]	0.0121 (3.93)[a]	-0.0139 (-3.15)[a]	-0.0205 (-3.69)[a]
WSJTEAM	0.0018 (1.01)	0.0014 (0.91)	0.0002 (0.07)	0.0053 (1.97)[b]
CEXP * 10^{-3}	0.0020 (4.31)[a]	0.0026 (6.99)[a]	0.0038 (6.51)[a]	0.0028 (3.93)[a]
NCOS * 10^{-3}	-0.0028 (-3.24)[a]	-0.0036 (-5.44)[a]	0.0028 (2.89)[a]	0.0028 (2.18)[b]
Number of Observations	19,440	28,665	28,618	19,632
Adj. R-square	0.034	0.020	0.027	0.034
P-value of F-test	0.000	0.000	0.000	0.000

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

Table 6

Abnormal Volume Surrounding Announcements of Revisions in Stock Recommendations by Analysts

The table shows cumulative abnormal trading volume surrounding revisions in analyst stock recommendations. Revisions are defined and classified as in Table 3. Abnormal volume for stock *i* on day *t* is computed using daily CRSP data as $e_{it} = v_{it} - v_i$ where v_{it} is volume on day t and where v_i is average volume over days -35 to -6 relative to the recommendation revision. All share volumes are normalized by dividing by common shares outstanding on the same day. T-statistics for the difference in mean values from zero are shown in parentheses below the means. P-values of the Wilcoxon test are shown in parentheses below median values. N denotes sample size.

	$CAV_{-1,0}$			$CAV_{-1,+1}$			$CAV_{-5,+5}$		
Recommendation Revision	Mean (t-stat)	Median (p-value)	*N*	Mean (t-stat)	Median (p-value)	*N*	Mean (t-stat)	Median (p-value)	*N*
Upgrades									
Added to Strong Buy	0.0086 (8.89)[a]	0.0011 (0.000)	24,506	0.0097 (8.18)[a]	0.0015 (0.000)	24,502	0.0071 (3.13)[a]	0.0030 (0.000)	24,488
Added to Buy/ Strong Buy	0.0053 (5.08)[a]	0.0002 (0.000)	36,800	0.0058 (4.54)[a]	0.0004 (0.000)	36,796	0.0020 (0.818)	0.0008 (0.000)	36,766
Downgrades									
Dropped from Buy/Strong Buy	0.0217 (114.47)[a]	0.0010 (0.000)	33,291	0.0265 (114.14)[a]	0.0014 (0.000)	33,232	0.0381 (85.70)[a]	0.0039 (0.000)	33,175
Dropped from Strong Buy	0.0259 (128.76)[a]	0.0017 (0.000)	22,808	0.0315 (127.86)[a]	0.0025 (0.000)	22,779	0.0453 (96.03)[a]	0.0057 (0.000)	22,756

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

Table 7

Abnormal Trading Volume Over Days -1 to +1 Surrounding Revisions in Stock Recommendations by Analysts with Differing Degrees of Potential Conflict

The sample of recommendation revisions covers the period 1994-2003 and is obtained from the I/B/E/S U.S. Detail Recommendations History file. Revisions are defined and classified as in Table 3. Investment banking revenue and commission revenue are measured at the end of the latest fiscal year preceding a recommendation change. Median values for investment banking and commission revenue fractions are computed across all firm-year observations in the sample. Abnormal volume for stock *i* on day *t* is computed using daily CRSP data as $e_{it} = v_{it} - v_i$ where v_{it} is volume on day t and where v_i is average volume over days -35 to -6 relative to the recommendation revision. All share volumes are normalized by dividing by common shares outstanding. T-statistics are for differences in means and p-values are from the Wilcoxon test for differences in distributions.

Panel A: Investment Banking Revenue								
	Mean CAV			Median CAV			Number of Obs.	
Recommendation Revision	IB% above median	IB% below median	|t-stat.|	IB% above median	IB% below median	p-value	IB% above median	IB% below median
Upgrades								
Added to Strong Buy	0.0102	0.0081	2.04[b]	0.0020	0.0006	0.000	16,790	7,085
Added to Buy/ Strong Buy	0.0058	0.0055	0.26	0.0005	0.00001	0.000	25,685	10,239
Downgrades								
Dropped from Buy/Strong Buy	0.0293	0.0189	8.36[a]	0.0019	0.0004	0.000	23,050	9,397
Dropped from Strong Buy	0.0349	0.0224	8.01[a]	0.0030	0.0011	0.000	15,743	6,495

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

Table 7 (cont.)

Panel B: Brokerage Commission Revenue								
	Mean CAV			Median CAV			Number of Obs.	
Recommendation Revision	COM% above median	COM% below median	|t-stat.|	COM% above median	COM% below median	p-value	COM% above median	COM% below median
Upgrades								
Added to Strong Buy	0.0089	0.0098	0.80	0.0003	0.0019	0.000	5,422	18,453
Added to Buy/ Strong Buy	0.0052	0.0059	0.31	-0.0003	0.0005	0.000	7,408	28,516
Downgrades								
Dropped from Buy/Strong Buy	0.0219	0.0274	3.93[a]	0.0006	0.0016	0.000	6,598	25,849
Dropped from Strong Buy	0.0242	0.0333	5.34[a]	0.0012	0.0027	0.000	5,066	17,172

Table 8

Cross-sectional Regressions of Abnormal Volume Surrounding Recommendation Revisions

Each column in the table shows the results of a cross-sectional OLS regression explaining cumulative abnormal share volume over days -1 to +1 surrounding a particular type of recommendation revision. Revisions are defined and classified as in Table 3. Share volume is normalized by dividing by the number of shares outstanding. IB% (COM%) is the percentage of total revenues derived from investment banking (brokerage commissions). LFIRM is an indicator variable equal to one if a brokerage house is a large firm (i.e., in the top quartile of all houses) as measured by the number of analysts issuing I/B/E/S stock recommendations in a given calendar year. CSIZE is the natural logarithm of a followed company's market capitalization, measured 12 months prior to the end of the current month. IITEAM (WSJTEAM) is an indicator variable equal to one if the recommending analyst was listed as an All-American (All-Star) in the most recent *Institutional Investor* (*Wall Street Journal*) annual analyst survey. CEXP is the number of days that an analyst has been issuing research on I/B/E/S (including any forecasts or recommendations) on a company. NCOS equals the number of companies followed by an analyst in the current calendar year. All regressions include calendar-year and I/B/E/S 2-digit industry dummies (not reported). T-statistics are reported in parentheses below coefficient estimates.

Explanatory Variable	Added to Strong Buy	Added to Buy/ Strong Buy	Dropped from Buy /Strong Buy	Dropped from Strong Buy
Intercept	0.0045 (0.08)	-0.0002 (-0.00)	0.0705 (0.67)	0.0695 (0.65)
IB%	-0.0102 (-2.74)[a]	-0.0089 (-3.17)[a]	0.0135 (2.24)[b]	0.0298 (3.95)[a]
COM%	-0.0060 (-2.98)[a]	-0.0062 (-4.12)[a]	0.0090 (2.90)[a]	0.0055 (1.50)
LFIRM	0.0057 (5.09)[a]	0.0039 (4.58)[a]	0.0169 (9.97)[a]	0.0169 (8.42)[a]
CSIZE	-0.0028 (-11.67)[a]	-0.0016 (-8.78)[a]	-0.0021 (-5.85)[a]	-0.0037 (-8.21)[a]
IITEAM	0.0040 (1.47)	0.0036 (1.77)	0.0077 (2.10)[b]	0.0048 (1.03)
WSJTEAM	0.0014 (1.06)	0.0017 (1.71)	0.0012 (0.63)	-0.0008 (-0.35)
CEXP * 10^{-3}	0.0004 (1.25)	0.0006 (2.59)[a]	-0.0034 (-7.02)[a]	-0.0034 (-5.57)[a]
NCOS * 10^{-3}	-0.0015 (-2.51)[b]	-0.0018 (-4.23)[a]	-0.0013 (-1.67)	-0.0007 (-0.65)
Number of Obs.	19,431	28,653	28,594	19,619
Adj. R-square	0.022	0.015	0.028	0.042
P-value of F-test	0.000	0.000	0.000	0.000

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

Table 9

Medium-Term Investment Performance of Revisions in Analyst Stock Recommendations

The table shows abnormal returns to portfolios formed on the basis of analyst recommendation revisions. Revisions are defined and classified as in Table 3. We construct an equal-weighted portfolio consisting of all stocks experiencing a particular type of recommendation revision (e.g., added to strong buy) in each calendar month in the sample. A stock that enters a portfolio because it was added to (dropped from) a particular recommendation category is removed from the portfolio when it is dropped from (added to) the category. We estimate the following cross-sectional OLS regression for month 0 (month of the revision):

$$R_p - R_f = \alpha + \beta_1 (R_m - R_f) + \beta_2 SMB + \beta_3 HML + \varepsilon, \text{ p=1, 2, …, n calendar month portfolios,}$$

where R_p is the month 0 return for portfolio p and where $R_m - R_f$, SMB, and HML are monthly returns on the Fama and French (1993) factors. The estimate of α is the abnormal return for month 0. We repeat this regression for months +1, +2, …, +12 relative to the month of portfolio formation to obtain abnormal monthly returns α_1, α_2, …, α_{12}, that are aggregated to obtain cumulative abnormal returns. N denotes the average number of calendar-month portfolios used in monthly regressions.

Portfolio	Month 0				Months +1 to +3				Months +1 to +6				Months +1 to +12		
	CAAR	t-stat	*N*		CAAR	t-stat	*N*		CAAR	t-stat	*N*		CAAR	t-stat	*N*
Added to Strong Buy	0.0331	13.77[a]	115		0.0146	4.03[a]	113		0.0184	3.55[a]	111.5		0.0120	1.37	108.5
Added to Buy/Strong Buy	0.0304	14.01[a]	115		0.0086	2.73[a]	113		0.0097	2.11[b]	111.5		-0.0024	-0.33	108.5
Dropped from Buy/ Strong Buy	-0.0474	-15.45[a]	115		-0.0166	-2.90[a]	113		-0.0317	-3.67[a]	111.5		-0.0504	-4.09[a]	108.5
Dropped from Strong Buy	-0.0495	-13.75[a]	115		-0.0205	-3.73[a]	113		-0.0404	-4.78[a]	111.5		-0.0675	-5.57[a]	108.5

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

Table 10

Medium-Term Investment Performance By Sources of Analyst Employer Revenues

The table shows abnormal returns to portfolios based on recommendation revisions by analysts employed by firms with above or below median (Q_2) percentage of revenue from investment banking (IB%) or brokerage commissions (COM%). Revisions are defined and classified as in Table 3. We construct an equal-weighted portfolio consisting of all stocks experiencing a particular type of recommendation revision by a group of analysts (e.g., added to strong buy by analysts with IB% > Q_2) in each calendar month in the sample. A stock remains in a portfolio until the recommendation is changed again. We estimate the following cross-sectional OLS regression for month +1 (one month after the revision month):

$$R_p - R_f = \alpha + \beta_1 (R_m - R_f) + \beta_2 SMB + \beta_3 HML + \varepsilon, \text{ p=1, 2, …, n calendar month portfolios,}$$

where R_p is the month +1 return for portfolio p and where R_m -R_f, *SMB*, and *HML* are monthly returns on the Fama and French (1993) factors. The estimate of α is the average abnormal return for month +1. We repeat this regression for months +2, +3, …, +12 to obtain abnormal returns for each of those months. Monthly average abnormal returns are aggregated to obtain cumulative average abnormal returns (CAAR). Each cell shows the CAAR, its t-statistic for the difference from zero in parentheses, and the average number of calendar-month portfolios used in monthly regressions in square brackets.

Panel A: Investment Banking Revenue

	Months +1 to +3			Months +1 to + 6			Months +1 to + 12		
Portfolio	IB% > Q_2	IB% ≤ Q_2	| t-stat |	IB% > Q_2	IB% ≤ Q_2	| t-stat |	IB% > Q_2	IB% ≤ Q_2	| t-stat |
Added to Strong Buy List	0.0165 (3.962)[a] [113]	0.0156 (3.044)[a] [108]	0.136	0.0250 (4.248)[a] [111.5]	0.0127 (1.691) [106.5]	1.289	0.0166 (1.717) [108.5]	0.0203 (1.671) [103.5]	0.238
Added to Buy/Strong Buy List	0.0104 (3.002)[a] [113]	0.0056 (1.212) [108]	0.831	0.0130 (2.607)[a] [111.5]	0.0050 (0.745) [106.5]	0.957	-0.0054 (-0.688) [108.5]	0.0121 (1.194) [103.5]	1.365
Dropped from Buy/Strong Buy List	-0.0183 (-2.738)[a] [113]	-0.0180 (2.836)[a] [109]	0.033	-0.0349 (-3.566)[a] [111.5]	-0.0311 (-3.196)[a] [107.5]	0.275	-0.0572 (-4.222)[a] [108.5]	-0.0412 (-2.939)[a] [104.5]	0.821
Dropped from Strong Buy List	-0.0264 (-4.275)[a] [113]	-0.0097 (-1.349) [109]	1.762	-0.0471 (-5.011)[a] [111.5]	-0.0249 (-2.332)[b] [107.5]	1.561	-0.0742 (-5.546)[a] [108.5]	-0.0535 (-3.547)[a] [104.5]	1.027

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

Table 10 (cont.)

Panel B: Brokerage Commission Revenue									
	Months +1 to +3			Months +1 to + 6			Months +1 to + 12		
Portfolio	COM% > Q_2	COM% <= Q_2	| t-stat |	COM% > Q_2	COM% <= Q_2	| t-stat |	COM% > Q_2	COM% <= Q_2	| t-stat |
Added to Strong Buy List	0.0098 (1.436) [105]	0.0160 (4.278) [113]	0.797	0.0009 (0.091) [103.5]	0.0226 (4.284) [111.5]	1.305	-0.0181 (-1.132) [100.4]	0.0169 (1.901) [108.5]	1.913
Added to Buy/Strong Buy List	0.0012 (0.202) [105]	0.0094 (2.855) [113]	1.207	-0.0024 (-0.254) [103.5]	0.0108 (2.336) [111.5]	0.763	-0.0084 (-0.584) [100.4]	-0.0035 (-0.474) [108.5]	0.303
Dropped from Buy/Strong Buy list	-0.0182 (-2.201) [103]	-0.0179 (-3.090) [113]	0.030	-0.0234 (-1.817) [101.5]	-0.0359 (-4.124) [111.5]	0.731	-0.0328 (-1.801) [98.5]	-0.0566 (-4.544) [108.5]	1.079
Dropped from Strong Buy List	-0.0112 (-1.440) [103]	-0.0234 (-4.174) [113]	1.272	-0.0296 (-2.402) [101.5]	-0.0448 (-5.177) [111.5]	0.666	-0.0516 (-2.898) [98.5]	-0.0712 (-5.697) [108.5]	0.901

Table 11
Cross-Sectional Regressions of Medium-Term Performance of Recommendation Revisions

Each column in the table shows the results of a cross-sectional OLS regression of abnormal stock returns over months +1 to +12 following a particular type of recommendation revision. Revisions are defined and classified as in Table 3. Abnormal returns are computed as the intercept from time-series regressions of monthly stock returns on Fama and French factors for each firm. IB% (COM%) is the percentage of a firm's total revenues derived from investment banking (brokerage commissions). LFIRM is an indicator variable equal to one if a brokerage house is a large firm (i.e., in the top quartile of all houses) as measured by the number of analysts issuing I/B/E/S stock recommendations in a given calendar year. CSIZE is the natural logarithm of a followed company's market capitalization, measured 12 months prior to the end of the current month. IITEAM (WSJTEAM) is an indicator variable equal to one if the recommending analyst was listed as an All-American (All-Star) in the most recent *Institutional Investor* (*Wall Street Journal*) annual analyst survey. CEXP is the number of days that an analyst has been issuing research on a company (including forecasts and recommendations) according to I/B/E/S. NCOS equals the number of companies followed by an analyst in the current calendar year. T-statistics are reported in parentheses below coefficient estimates. Regressions include calendar year and I/B/E/S 2-digit S/I/G industry code dummies (not reported). Observations involving revisions that occur within 12 months of an earlier revision on the stock are omitted from the regressions.

Explanatory Variable		Added to Strong Buy		Added to Buy/ Strong Buy		Dropped from Buy /Strong Buy		Dropped from Strong Buy
Intercept		0.0505 (3.44)[a]		0.0076 (0.58)		-0.0637 (-0.88)		-0.0810 (-1.14)
IB%		-0.0084 (-1.14)		-0.0012 (-0.18)		0.0043 (0.61)		-0.0065 (-0.82)
COM%		0.0062 (1.43)		0.0056 (1.58)		0.0056 (1.53)		0.0030 (0.77)
LFIRM		0.0011 (0.49)		-0.0025 (-1.29)		0.0016 (0.87)		0.0015 (0.77)
CSIZE		-0.0013 (-2.56)[b]		-0.0018 (-4.16)[a]		-0.0007 (-1.67)		-0.0007 (-1.46)
IITEAM		-0.0034 (-0.61)		-0.0006 (-0.12)		-0.0017 (-0.39)		-0.0010 (-0.22)
WSJTEAM		0.0028 (1.07)		-0.0002 (-0.09)		-0.0028 (-1.31)		0.0057 (2.45)[b]
CEXP * 10^{-3}		0.0008 (1.16)		0.0012 (2.07)[b]		0.0001 (0.09)		0.0003 (0.56)
NCOS * 10^{-3}		-0.0057 (-1.20)		-0.0080 (-2.01)[b]		-0.0036 (-1.19)		-0.0043 (-1.13)
Number of Obs.		6,411		8,851		10,644		8,368
Adj. R-square		0.022		0.021		0.017		0.017
P-value of F-test		0.000		0.000		0.000		0.000

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

Table 12

Regressions of Recommendation Levels, Abnormal Returns, Abnormal Volume and Stock Performance For Bubble versus Post-Bubble Periods

Panel A shows the results of an ordered probit regression of recommendation levels on the explanatory variables in model 1 of Table 2, except that (1) IB% and COM% are interacted with binary variables BUBBLE and POST, indicating the bubble or post-bubble period, and (2) calendar-quarter dummies are replaced with a post-regulation indicator (equal to 1 for quarters after May 2002). Panel B shows the results of ordinary-least-squares regressions explaining abnormal announcement stock returns, abnormal announcement volume, and abnormal 1-year performance of recommendation revisions by the explanatory variables used in Tables 5, 8, and 11, except that IB% and COM% are interacted with BUBBLE and POST. The table reports coefficient estimates for only these four interaction variables in each regression. Also reported are p-values from t-tests for IB%*BUBBLE versus IB%*POST and for COM%*BUBBLE versus COM%*POST.

Panel A: Ordered Probit Regression of Recommendation Levels

	Bubble	Post-Bubble	p-value
IB%	0.8299	0.3530	< 0.001
COM%	-0.1357	0.2444	< 0.001

Panel B: Ordinary Least Squares Regressions of Abnormal Returns, Abnormal Volume, and Abnormal Stock Performance

	Added to Strong Buy			Added to Buy/Strong Buy			Dropped from Buy/Strong Buy			Dropped from Strong Buy		
	Bubble	Post-Bubble	p-value	Bubble	Post-Bubble	p-value	Bubble	Post-Bubble	p-value	Bubble	Post-Bubble	p-value
Regressions of three-day abnormal returns (CAR for days -1 to +1)												
IB%	-0.0252[a]	-0.0084	0.029	-0.0149[a]	0.0026	0.006	-0.0152	-0.0258[a]	0.306	-0.0380[a]	-0.0179[b]	0.125
COM%	-0.0118[a]	-0.0094[a]	0.483	-0.0115[a]	-0.0080[a]	0.221	-0.0074	-0.0163[a]	0.053	0.0014	-0.0042	0.310
Regressions of three-day abnormal volume (CAV for days -1 to +1)												
IB%	-0.0082	-0.0043	0.478	-0.0081[b]	-0.0038	0.308	0.0258[a]	0.0105	0.078	0.0559[a]	0.0089	0.000
COM%	-0.0045[b]	-0.0007	0.114	-0.0063[a]	-0.0020	0.020	0.0111[a]	0.0133[a]	0.5742	0.0046	0.0119[a]	0.114
Regressions of 12-month stock performance (CAR for months +1 to +12)												
IB%	0.0153	-0.0083	0.248	0.0105	0.0006	0.597	0.0084	0.0044	0.844	0.0209	-0.0133	0.124
COM%	0.0080	0.0068	0.905	0.0155	0.0071	0.307	0.0120	0.0080[b]	0.631	0.0096	0.0030	0.461

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