

Using Counter-explanation to Limit Unintentional Optimism in Analysts' Forecasts

Kathryn Kadous
Emory University
Goizueta Business School
1300 Clifton Road
Atlanta, GA 30322
kathryn_kadous@bus.emory.edu

Susan D. Krische
University of Illinois at Urbana-Champaign
1206 S. Sixth Street
Champaign, IL 61820
krische@uiuc.edu

Lisa M. Sedor
University of Notre Dame
102 Mendoza College of Business
Notre Dame, IN 46556
Lisa.M.Sedor.1@nd.edu

July 2004

We thank Michael Bamber, Walt Blacconiere, Ken Gaver, Jackie Hammersley, Lauren Maines, Jamie Pratt, Dave Ricchiute, Jerry Salamon, Nathan Stuart, Mike Tiller, Michael Williamson, Alex Yen, workshop participants at the 9th Behavioral Decision Making Research in Management conference, the 2004 Canadian Academic Accounting Association annual meeting, Indiana University, the University of Florida, and the University of Georgia for helpful comments; David Cantos, Jim Frederickson, Oliver Li, Jeff Miller, Dave Ricchiute, and Sandra Vera-Munoz for help with developing our materials; and Andrew Litten for research assistance.

Using Counter-explanation to Limit Unintentional Optimism in Analysts' Forecasts

ABSTRACT: Prior research demonstrates that forecast optimism is, in part, an unintentional consequence of analysts' cognitive reactions to the scenarios managers use to communicate future plans. In two experiments, we examine whether counter-explanation (explaining why managers' plans could fail) limits unintentional forecast optimism. We find that, when compared to analysts who do not generate counter-explanations, analysts who complete the relatively easy task of generating few counter-explanations make less optimistic forecasts, but analysts who complete the relatively difficult task of generating many counter-explanations do not. Results suggest boundary conditions for the effective use of counter-explanation to limit scenario-induced forecast optimism.

Keywords: *counter-explanation; availability; EPS; forecast optimism.*

Data availability: *Contact the authors.*

I. INTRODUCTION

In a move applauded by Wall Street analysts, Coca-Cola Co. announced that it would no longer provide quarterly earnings guidance because such short-run guidance, "...prevents a more meaningful focus on the strategic initiatives that a company is taking to build its business and succeed over the long run" (*Wall Street Journal*, December 13, 2002). A dozen major corporations recently followed suit (Byrnes 2003), and nearly 20% of NIRI-member firms report that they have considered eliminating the provision of earnings guidance (NIRI 2003). Managers eliminating short-run earnings guidance to promote a focus on long-run performance likely will increase their use of qualitative or narrative communications regarding their plans and future earnings expectations.¹ Yet, when managers use detailed, causal narratives (i.e., scenarios) to communicate plans to improve future earnings, unintentional optimism in analysts' annual earnings forecasts results (Sedor 2002). Because investors do not completely unravel analysts' optimism (Huberts and Fuller 1995; Ackert and Athanassakos 1997; Rajan and Servaes 1997; Dechow et al. 2000; Bradshaw et al. 2003), increasing analysts' focus on managers' long-run strategic initiatives also increases the importance of limiting unintentional forecast optimism.

Providing information about managers' plans structured in scenarios facilitates analysts' ability to envision how and why managers' plans will improve future firm performance (i.e., engage in scenario thinking). Scenario thinking inflates analysts' beliefs about the likelihood that the future performance improvements will occur, and unintentional forecast optimism results (Sedor 2002). Structuring managers' communications with analysts in contrived, non-scenario forms would limit the optimism induced by scenario thinking. However, managers are unlikely to alter communication structures to reduce analysts' unintentional optimism because managers

naturally use scenarios to communicate their plans (Tasker 1998) and have incentives to create favorable long-term outlooks for their firms (Kahn and Rudd 1999).

Instead, we propose that increasing analysts' awareness of the uncertainty inherent in the scenarios described by managers will increase the salience and perceived likelihood of alternative (less positive) outcomes, thus reducing unintentional forecast optimism. One means of increasing the salience of alternative outcomes is to ask analysts to generate counter-explanations: to list reasons why managers' plans could fail. Generating counter-explanations will enhance the perceived availability and salience of information that does not support managers' depicted outcome (Koonce 1992), weaken the causal links between managers' plans and the depicted outcome (Lipe 1991; Kennedy 1995), and thus, reduce the perceived likelihood of that outcome (Einhorn and Hogarth 1986; Heiman 1990).

Existing accounting research implies that the larger the number of counter-explanations considered by analysts, the greater the reduction in unintentional forecast optimism (Heiman 1990). However, asking analysts to generate a large number of counter-explanations is likely to increase task difficulty, and we expect that the ease or difficulty that analysts experience during a counter-explanation task will influence the effectiveness of this mechanism (Sanna et al. 2002). Specifically, we propose that counter-explanation will be effective at limiting unintentional forecast optimism when analysts generate counter-explanations with relative ease, but not when analysts generate counter-explanations with relative difficulty.

In Experiment 1, we provide sell-side analysts with summarized financial information and a scenario describing managers' plans to improve future earnings for a firm reporting prior losses. We focus on a loss firm because many firms that have discontinued earnings guidance

¹ For example, the NIRI (2003, Questions 2.12 and 3.1) survey suggests that managers may distinguish between "earnings guidance" and "other forms of guidance" that would provide relevant information for earnings estimates

reported recent losses (Graham, Harvey, and Rajgopal 2004), and because the influence of scenario thinking on analysts' earnings forecasts is larger for firms reporting recent losses than for firms reporting recent profits (Sedor 2002). We ask control condition participants to read information about the firm and to provide one- and two-year-ahead annual earnings forecasts. In contrast, we ask participants in experimental conditions to generate counter-explanations (i.e., to list reasons why managers' plans could fail) prior to providing their forecasts. We manipulate the difficulty participants experience while generating counter-explanations by asking them to list either few (which is relatively easy) or many (which is relatively difficult) counter-explanations. Results suggest that counter-explanation reduces unintentional optimism in participants' annual earnings forecasts when participants experience the task as relatively easy, but not when participants experience the task as relatively difficult.

In Experiment 2, we replicate Experiment 1 results with MBA-student participants. We also provide evidence that the experienced ease or difficulty of generating counter-explanations (i.e., their availability (Tversky and Kahneman (1973)) and not variations in counter-explanation strength, is driving results. Specifically, we ask some participants to read the few and many counter-explanations generated by other participants (i.e., making all counter-explanations equally available) prior to providing annual earnings forecasts. We find that all participants who read counter-explanations generated by others make relatively less optimistic forecasts than do control condition participants, although this effect is significant only for two-year-ahead forecasts. If variations in counter-explanation strength were driving experimental results, only forecasts made by participants who read the few counter-explanations should have been less optimistic, mirroring the results for the generation task.

using qualitative (instead of quantitative) information.

This study is the first that we know of to provide evidence on a cognitive mechanism (i.e., counter-explanation) that limits the unintentional forecast optimism induced by scenario thinking. We examine the use of a cognitive mechanism to constrain this optimism in order to match the debiasing mechanism to the source of the bias (Arkes 1991; Bonner et al. 1996; Kennedy 1993 and 1995). Additionally, our evidence suggests that there are boundary conditions for the effectiveness of counter-explanation tasks in reducing the effect of cognitive biases. Specifically, the debiasing influence of counter-explanation tasks may be limited when the counter-explanation task itself is experienced as difficult by the decision maker.

We use experiments to investigate the effectiveness of counter-explanation on limiting analysts' forecast optimism because archival data neither provide information regarding the forecasting processes used by financial analysts nor a control condition against which to compare the effects of requiring analysts to engage in counter-explanation tasks that vary in difficulty. Additionally, the experiments hold constant investment banking incentives, which enables us to examine how unintentional sources of forecast optimism are affected by counter-explanation. A limitation of an experimental approach is that we cannot measure absolute levels of forecast optimism, and thus the evidence is limited to *relative* levels of optimism across experimental conditions.

The remainder of this paper is organized as follows. Section II analyzes relevant literature and develops the hypotheses. Section III describes the design, method, and results for Experiment 1, and Section IV does the same for Experiment 2. The final section summarizes and concludes.

II. LITERATURE ANALYSIS AND HYPOTHESES

Forecast Optimism, Scenario Thinking, and Firm Performance

Optimism in annual earnings forecasts is statistically and economically significant (e.g., Richardson et al. 2002; Darrrough and Russell 2002; Duru and Reeb 2002). Forecast optimism also increases over the forecast horizon: analysts' two-year-ahead forecasts are relatively more optimistic than their one-year-ahead forecasts (DeBondt and Thaler 1990; Frankel and Lee 1998; Bradshaw et al. 2003), although optimism in quarterly earnings forecasts decreases as the earnings announcement date approaches (e.g., Brown 1997, 2001; Matsumoto 2002). Despite the tendency of analysts to reduce forecast optimism as the earnings announcement date approaches, market participants use forecasts of annual earnings to make investment decisions and to estimate firm value.² Thus, reducing optimism in analysts' long-term forecasts is likely to improve the quality of investors' decisions.

Many explanations for optimism in analysts' earnings forecasts have been offered. Analysts may issue intentionally optimistic forecasts because of incentives to maintain access to managers' private information (Francis and Philbrick 1993; Krishnan and Sivaramakrishnan 1998; Lim 2001), to motivate stock trades (Kim and Lustgarten 1998), to benefit stocks held by in-house mutual funds (Irvine et al. 1998), and to obtain or maintain investment banking business (Dugar and Nathan 1995; Hunton and McEwen 1997; Lin and McNichols 1998; Dechow et al. 2000; Bradshaw et al. 2003). Other explanations for optimistic forecasts include justifying favorable stock recommendations (Eames et al. 2002), failing to sufficiently adjust for earnings management (Abarbanell and Lehavy 2003), and choosing to report only on stocks that are

² Empirical applications of the residual income model often use analysts' forecasts as proxies for the market's expectations of future earnings (e.g., Dechow et al. 1999; Frankel and Lee 1998; Lee et al. 1999; Liu and Thomas 2000; Sougiannis and Yaekura 2001; Ali et al. 2003). Bradshaw (2004) suggests that analysts' recommendations

viewed favorably (McNichols and O'Brien 1997). Although the extent to which the forecast optimism observed in archival studies is intentional versus unintentional remains an empirical question, it is likely that at least some unintentional optimism occurs. Market analysts (Darrough and Russell 2002), analysts employed by independent research firms (Jacob et al. 2003), and students (Affleck-Graves et al. 1990), all of whom presumably lack incentives for optimism, make biased earnings forecasts. Additionally, recent research presents evidence consistent with the conclusion that analysts are unlikely to respond to trade-generating incentives by issuing upwardly-biased earnings forecasts (Irvine 2004) and moreover, that analysts are unlikely to issue intentionally optimistic forecasts (Eames and Glover 2003).

Unintentional optimism in analysts' annual earnings forecasts derives in part from analysts' cognitive reactions to the detailed, causal narratives (i.e., scenarios) that managers commonly use to communicate their plans to improve future firm performance (via conference calls, press releases, and other communications) (Sedor 2002).³ When individuals contemplate information structured in scenarios, they use scenario thinking (Dawes 1988). Using scenario thinking, analysts envision in concrete detail how managers will implement plans, and ultimately, how and why the managers expect those plans to improve future firm performance. Individuals use the ease of envisioning an outcome (Tversky and Kahneman 1973; Kahneman and Tversky 1982; Kahneman and Lovallo 1993) and the reasons why an outcome could occur (e.g., Hoch 1984; Levi and Pryor 1987) as cues when making probability assessments. Thus, scenario thinking inflates analysts' beliefs about the plausibility of managers' plans and the

reflect a simple heuristic based on forecasts of annual earnings and long-term earnings growth. Ohlson and Juettner-Nauroth (2000) also model value as a function of earnings and earnings growth forecasts.

³ Managers commonly use *narratives* to provide analysts with information about business strategies and their firms' future prospects (Francis et al. 1997) as well as to provide information about managers' plans (Tasker 1998) and the anticipated effects of those plans on future earnings (Previts et al. 1994).

likelihood that the specific, positive future outcomes described by managers (i.e., future performance improvements) will occur (Koehler 1991). Unintentional forecast optimism results.

The influence of scenario thinking on analysts' earnings forecasts is larger for firms reporting recent losses than it is for those reporting recent profits (Sedor 2002). This finding is consistent with the asymmetric pattern of optimism in analysts' annual earnings forecasts observed in archival studies: the most optimistic annual earnings forecasts are associated with firms that have weak prior earnings performance (Arbarbanell and Bernard 1992; Elgers and Lo 1994) or that report losses in the prior year (Klein 1990; Ali et al. 1992; Downen 1996).

Counter-explanation and Forecast Optimism

The influence of scenario thinking on analysts' forecasts implies that unintentional optimism in annual earnings forecasts likely would be reduced as the difficulty of envisioning the causal chain of events in which managers' plans lead to future performance improvements increases (e.g., by manipulating the structure of the information presented as in Sedor (2002)). However, such structural manipulations are unlikely in conference calls, press releases, or other managerial communications because managers naturally use scenarios to communicate their future plans (Tasker 1998) and have incentives to create favorable long-term outlooks for their firms (Kahn and Rudd 1999).

An alternative strategy is to increase analysts' awareness of the uncertainty inherent in the scenarios described by managers, thus increasing the salience and perceived likelihood of alternative (less positive) outcomes. One means of increasing the salience of alternative causal chains of events and outcomes is to ask analysts to generate counter-explanations (i.e., to list reasons why managers' plans could fail). We expect that generating counter-explanations will enhance the availability and salience of information in memory that does not support the positive

outcome depicted by managers (Koonce 1992), thus reducing the perceived likelihood of that outcome (Einhorn and Hogarth 1986; Heiman 1990). Additionally, we expect that generating counter-explanations will weaken the causal chains in the minds of analysts among current states, managers' plans, and improved future firm performance (Lipe 1991; Kennedy 1995).

In sum, we expect that counter-explanation will reduce the apparent inevitability of the specific, positive future outcome described by managers by requiring analysts to contemplate causal chains of events in which managers' plans fail to improve future earnings. However, we do not expect that analysts naturally generate sets of alternative causal chains of events with less positive outcomes when contemplating managers' plans. Prior research suggests that even professionals required by standards to be skeptical (i.e., auditors) do not appear to spontaneously generate counter-explanations (Heiman 1990; Koonce 1992). Moreover, we expect that there are boundary conditions for the effectiveness of counter-explanation tasks in reducing analysts' unintentional forecast optimism. In particular, we expect the availability of counter-explanations in analysts' memory to influence the extent to which a counter-explanation task affects their forecasts.

Experienced ease or difficulty of generating counter-explanations

There are two sources of information relevant to the use of items in memory, such as counter-explanations, for judgment tasks: the information content and the experienced ease or difficulty with which the information is brought to mind (Schwarz 1998). Individuals rely on the ease or difficulty of bringing information to mind as a valid cue (in addition to information content) when they consider themselves to be sufficiently knowledgeable in a domain (Schwarz 1998). Use of this information is consistent with the availability heuristic: individuals form

judgments of likelihood based upon the ease with which exemplars can be brought to mind (Tversky and Kahneman 1973).

Consistent with availability, we expect the ease with which counter-explanations are generated to influence their effectiveness in limiting the optimism induced by scenario thinking. In particular, we expect that analysts will infer the likelihood that the positive outcome described by managers (i.e., improved future firm performance) will occur from the extent of difficulty they experience while generating counter-explanations. If analysts generate counter-explanations with ease, they will infer from this experienced ease that the likelihood of alternative (less positive) outcomes is high. Consequently, analysts will infer that the likelihood of future performance improvements must be low, and unintentional forecast optimism will be reduced. On the other hand, if analysts generate counter-explanations with difficulty, they will infer from this experienced difficulty that there are not many feasible alternatives to the positive outcome described by managers. In this case, generating counter-explanations will be less effective in reducing unintentional forecast optimism, and may even increase it.

Consistent with this reasoning, in the context of de-biasing hindsight effects (i.e., exaggerated assessments of the inevitability of past events), Sanna et al. (2002) found that asking participants to generate a small number (2) of thoughts about how alternative outcomes could have occurred (which participants found easy to do) attenuated hindsight. However, asking participants to generate a large number (10) of thoughts (which participants found difficult to do) exacerbated hindsight effects, despite the fact that the latter group identified significantly more thoughts about how alternative outcomes could have occurred than did the former group.

Nevertheless, it is unclear whether the effects of counter-explanation observed by Sanna et al. (2002) in the context of debiasing hindsight will be observed in the context of debiasing

scenario thinking. Hindsight effects occur when individuals learn about a known outcome, update their mental models for the outcome, and elaborate causes that might have led up to it (Hawkins and Hastie 1990). Thus, hindsight effects appear to be induced by a process similar to diagnostic learning, which involves retrospectively revising an already-formed causal model in light of new outcome information (Waldmann 2000). In contrast, scenario thinking requires individuals to elaborate how planned actions might cause future outcomes—a process similar to predictive learning. In predictive learning, a mental model is successively updated in a way that parallels the unfolding of events over time (Waldmann 2000). Psychology research has demonstrated clear differences between predictive and diagnostic learning with identical learning trials (Waldmann 2001). Thus, we test the following predictions:

- H1:** Analysts who are asked to generate *few* counter-explanations of managers' plans to improve future earnings will make *less* optimistic earnings forecasts than will analysts who are not asked to generate counter-explanations.
- H2:** Analysts who are asked to generate *many* counter-explanations of managers' plans to improve future earnings will *not* make less optimistic earnings forecasts than will analysts who are not asked to generate counter-explanations.

III. EXPERIMENT 1

In Experiment 1, we examine whether unintentional optimism in analysts' earnings forecasts can be limited by generating counter-explanations and whether the ease with which counter-explanations are generated influences the effectiveness of this mechanism. We use a 1 x 3 between-subjects design with the number of counter-explanations participants are asked to generate (none, few, many) as independent variables. The primary dependent variable is participants' forecast increases in annual earnings.

Design and Method

Participants

Participants are 59 financial analysts that we recruited from the 2003 *Nelson's Directory of Investment Research*.⁴ The participants have a mean (median) of 11 (8) years of experience; 93 percent are sell-side analysts, 36 percent are certified financial analysts (CFAs), and 37 percent have been named as All-Star Analysts. Participants reported a mean (median) of 1.4 (1.0) industry specializations, with the most common being entertainment (19%), telecommunications (19%), health (10%), and transportation (10%).⁵ We used a predetermined randomization plan to assign participants to experimental conditions as they were recruited. We provided each participant with an electronic link to the experimental materials for his or her assigned condition, and participants completed the study on-line.

Case Materials and Procedures

We adapted our materials from Sedor (2002).⁶ We focus on Sedor's loss scenario condition because that is the condition in which limiting unintentional optimism in analysts' annual earnings forecasts likely is most useful.

Participants were instructed to imagine they were initiating coverage of a fictional company (Villa Fiore Winery) that did not have, and did not contemplate having, an investment

⁴ Participants were recruited via telephone by the researchers. As a token of our appreciation for their participation, analysts could opt into a drawing for shipment of fine wines (where allowed by law) or the equivalent cash value of \$500.

⁵ Including the researcher who recruited the analyst, years of experience, CFA designation, or All-Star Analyst rating, as an additional covariate when testing our hypotheses does not change reported inferences. Additionally, inferences remain unchanged if data from buy-side analysts or the analyst who indicated a beverage specialization are excluded.

⁶ Advantages of these materials include (1) at (and before) the time the experiment was conducted, the press had not reported any noteworthy news events for the wine industry (e.g., excessive supplies, recalls), (2) the wine industry is not followed by a large number of analysts (minimizing any potential advantage of industry-specific expertise), and (3) these materials reliably induced participants to engage in scenario thinking in Sedor (2002).

banking relationship with the participant's brokerage firm.⁷ Participants read three years of summarized financial information (including net losses and negative earnings per share (EPS) for the current and prior two years), a brief description of the company, and product information before making preliminary forecasts of annual EPS for one and two years ahead.⁸ Participants' forecasts were elicited on a separate screen following the presentation of the company's financial information. In general, participants were unable to move backwards as they progressed through the experimental materials. However, participants were able to review (via an electronic link) the company's financial information when making their preliminary forecasts.

Next, participants read excerpts from a conference call held after the company's annual earnings announcement, generated counter-explanations (if applicable), and then revised their preliminary forecasts. The conference call excerpts included the CEO's discussion of the industry, the company, and a description of managers' plans to improve future earnings in scenario structure (see Appendix). Participants were able to review (via an electronic link) the company's financial information and/or the conference call excerpts (but not their counter-explanations, if applicable) when making their revised forecasts. Finally, participants completed a post-experimental questionnaire.

Independent Variables

We asked participants in experimental conditions to generate counter-explanations after they read the conference call excerpt, but before they made their revised forecasts. Specifically,

⁷ No prior or contemplated investment banking relationship ensures that investment banking incentives do not influence participants' forecasts and equalizes participants' assumptions about these incentives across experimental conditions. A post-experimental question confirms that all (100%) of the participants correctly assumed that their firm did not have, and did not contemplate having, an investment banking relationship with the company being analyzed.

⁸ Participants also forecasted long-term growth (LTG) for the three years after the two-year-ahead forecast. Although the pattern of LTG forecasts matches that of EPS forecasts, our manipulations do not explain significant

participants in the generate few (generate many) conditions received the following additional instruction:

Imagine that firm policy requires you to document (as part of your analysis) reasons why managers' plans COULD FAIL. Below, please provide TWO (TWELVE) reasons why the plans presented by Villa Fiore's managers during the conference call COULD FAIL to increase sales and profitability as expected.

The on-line materials included either two or twelve blank lines for participants' counter-explanations, depending on experimental condition. The instrument was programmed such that participants were required to input the requested number of counter-explanations before proceeding to the next screen. Control condition participants were not asked to generate counter-explanations and revised their forecasts immediately after reading the conference call excerpts.

Dependent Measures

Participants provided preliminary and revised forecasts of annual EPS for one and two years ahead of current (year 0) EPS of $-\$0.64$. We calculate the primary dependent measures (forecast increases in EPS) by subtracting the current EPS from participants' revised EPS forecasts for both one (year 1) and two years ahead (year 2). We use participants' preliminary forecast increases as covariates in our analyses.

We use participants' responses to relevant post-experimental questions as manipulation checks. Several participants failed to respond to one or more questions. We base each analysis on the maximum number of useable responses.

Results

Preliminary Analyses

We exclude three participants' forecast increases in EPS from the data analyses because they differed from sample means by more than four standard deviations, and DFFITS and DFBETA

variation in the LTG forecasts (smallest $p=0.080$). We believe this occurs because of the inherent difficulty in

procedures identify them as influential outliers. Thus, reported analyses use the remaining 56 observations.⁹

We expected reading the conference call excerpts in scenario structure to facilitate participants' ability to engage in scenario thinking, to inflate participants' beliefs about the likelihood that managers' plans would improve future earnings, and consequently to drive upward revisions in participants' preliminary forecasts, on average. Consistent with this, control condition participants made revised forecasts that exceeded their preliminary forecasts by \$0.07 for year 1 ($t_{16} = 1.39, p = 0.09$) and by \$0.10 ($t_{16} = 2.01, p = 0.03$) for year 2.

Manipulation Check

In a post-experimental question, we asked participants who generated counter-explanations to rate how difficult it was for them to do so using a scale ranging from 1 (Not at all difficult) to 9 (Extremely difficult). Consistent with a successful manipulation, participants asked to generate twelve counter-explanations found the task more difficult than did participants asked to generate two counter-explanations (means [standard deviations] are 3.67 [2.16] and 1.88 [1.30] for the generate many and generate few conditions, respectively; $t_{37} = 3.25, p < 0.01$).

Tests of Hypotheses

Table 1, Panel A reports adjusted means, standard deviations, and cell sizes for forecast increases in EPS for years 1 and 2. We compare the forecasts of experimental participants to those of participants not asked to generate counter-explanations (i.e., control condition

forecasting a long-term growth rate for a firm with negative earnings.

⁹ Although approximately equal numbers of participants were assigned to each condition, and approximately equal numbers of participants in each condition accessed the study, participants in the generate many condition were marginally less likely to complete both sets of forecasts than participants in the other two conditions ($\chi^2 = 5.12, p = 0.08$), and thus the cell size for the generate many condition is the smallest. However, of the 16 participants who dropped out before completing the study, 12 did so before making preliminary forecasts. These participants could not have seen the counter-explanation manipulation that took place after preliminary forecasts were elicited. Fisher's Exact Test reveals that the timing of dropouts does not differ by experimental condition ($p = 0.73$) and thus, it is unlikely that manipulation differences caused differences in drop outs across experimental conditions.

participants) to determine whether the effectiveness of counter-explanation at limiting unintentional optimism is moderated by the ease or difficulty experienced during the counter-explanation task. Table 1, Panel B reports results of the planned contrasts used to test our hypotheses. Participants asked to generate few counter-explanations made less optimistic EPS forecasts than did control condition participants ($t_{55} = 2.09, p = 0.02$ and $t_{55} = 1.92, p = 0.03$ for year 1 and year 2, respectively), supporting Hypothesis 1. Participants asked to generate many counter-explanations did not make less optimistic EPS forecasts than did control condition participants ($t_{55} = 0.68, p = 0.51$ for year 1 and $t_{55} = 0.95, p = 0.35$ for year 2), and Hypothesis 2 is supported.

Tests of Alternative Explanations

We offer tests to rule out potential alternative explanations for the results. First, analysis of variance models reveal no significant relationship between experimental condition and perceptions about task realism, perceptions about the extent to which generating reasons why managers' plans could fail is a routine part of the forecasting process, beliefs about managerial competence, or beliefs about managerial honesty (p -values > 0.59 for all *omnibus* F-tests).

Second, differences in effort across conditions are unlikely to be driving results. In post-experimental questions, participants reported (a) the numbers of different ways that managers' plans could fail that they considered (mean [median] of 4.6 [4.0] on a scale ranging from 1 [Not very many] to 9 [Very many]); (b) the amount of attention they gave to each of the ways that managers' plans could fail (mean [median] of 5.1 [5.0] on a scale ranging from 1 [No attention] to 9 [A great deal of attention]); and (c) the importance of providing both favorable and accurate forecasts (mean [median] of 2.4 [1.5] and 5.8 [7.0] for favorability and accuracy, respectively, on

scales ranging from 1 [Not at all important] to 9 [Extremely important]). These ratings do not vary by experimental condition (p -values > 0.27 for all *omnibus* F-tests).

IV. EXPERIMENT 2

In Experiment 1, we found that generating few counter-explanations was effective in limiting unintentional optimism, although generating many counter-explanations was not. We attributed this difference in the ability of a counter-explanation task to limit analysts' unintentional optimism to differences in the availability of the counter-explanations in analysts' memory. However, we cannot rule out the possibility that Experiment 1 results are driven by recency or dilution effects (Wanke et al. 1996). If participants found the task to be difficult, counter-explanations could have become less convincing as the number of explanations generated increased; thus, it is possible that less-convincing counter-explanations were more accessible to participants in the generate many condition, diluting the debiasing effect of the more convincing counter-explanations that they generated earlier in the sequence. We perform Experiment 2 to replicate Experiment 1 results and to rule out this alternative explanation.

If all counter-explanations were equally available in analysts' memory (i.e., if only the content of the counter-explanations generated was considered as a valid cue, and not the difficulty experienced while generating counter-explanations), then we would expect that generating many counter-explanations would be at least as effective in limiting unintentional optimism as would be generating few counter-explanations. One way to ensure that counter-explanations are equally available in memory is to ask analysts to read counter-explanations instead of generating them. Further, if analysts read the counter-explanations generated by other analysts (in the same order), and results show that both reading few and reading many counter-explanations reduce unintentional optimism, these results would also suggest that Experiment 1

results were unlikely to have been driven by recency or dilution effects. We make the following unique predictions for Experiment 2:

- H3:** Analysts who are asked to read *few* counter-explanations of managers' plans to improve future earnings will make less optimistic earnings forecasts than will analysts who are not asked to generate or read counter-explanations.
- H4:** Analysts who are asked to read *many* counter-explanations of managers' plans to improve future earnings will make less optimistic earnings forecasts than will analysts who are not asked to generate or read counter-explanations.

Thus, in Experiment 2, we further explore whether the availability of counter-explanations influences the effectiveness of a counter-explanation task at limiting unintentional forecast optimism (i.e., replicate Experiment 1, Hypotheses 1 and 2), and examine the effectiveness of reading another participant's counter-explanations in reducing optimism (i.e., test Hypotheses 3 and 4). We manipulate the independent variables in a $(2 \times 2) + 1$ (control) between-subjects experiment with the task (generate or read counter-explanations) and the number of counter-explanations (few or many) as independent variables. Control condition participants neither generate nor read counter-explanations.

Design and Method

Participants

Participants are 131 second-year students enrolled in a managerial accounting class in a *Business Week* Top 25 MBA program.¹⁰ Participants were recruited via in-class announcements and a \$1,000 contribution was made to the MBA class gift as a token of our appreciation.

Approximately 89 percent of participants report having previous personal investment experience.

¹⁰ One of these participants provided inappropriate responses to the forecast question (providing percentages instead of dollar amounts), and so we eliminated that observation. Near the end of the participation period, eight MBA students who were not enrolled in the managerial accounting class (because they had previous coursework and were

Participants report having taken an average of four university-level accounting classes and three university-level finance classes.¹¹

Case Materials and Procedures

Our case materials are similar to those used in Experiment 1. One exception is that the net losses and EPS for the current and prior two years are less negative: materials for Experiment 2 report current (year 0) EPS of $-\$0.08$, instead of the $-\$0.64$ reported in Experiment 1. The procedures are identical to those used in Experiment 1, with the exception of the independent variable manipulations discussed below.¹²

Independent Variables

We asked participants to generate counter-explanations or to read the counter-explanations generated by other participants after they read the conference call excerpt, but before they made their revised forecasts. Specifically, participants in the generate few (generate many) conditions received the following additional instruction:

Before moving on to the next section, please list TWO (TEN) thoughts about how future financial performance might not be as positive as Villa Fiore expects. In other words, how might Villa Fiore's plans to increase sales and profitability fail?

The on-line materials included either two or ten blank lines for participants' counter-explanations, depending on experimental condition. To ensure that participants in the generate many condition did not have to struggle at length to generate the full set of ten counter-explanations, the instrument was programmed such that participants were required to input a

taking a shortened program) but were in the same MBA class asked to participate. They are included in the total of 131. All reported inferences are identical if data from these eight participants are omitted.

¹¹ Inferences are unchanged if data from participants with no prior investment experience are eliminated. Including total number of accounting classes, total number of finance classes, track within the MBA program, investment experience, or gender as an additional covariate in the analyses also does not change the reported inferences.

¹² MBA participants were also asked whether they had assumed that their firm had an investment banking relationship with Villa Fiore in a post-task question. Although participants were told in the materials that there was

minimum of two counter-explanations before proceeding. Control condition participants were not asked to generate any counter-explanations and revised their forecasts immediately after reading the conference call excerpts.

Participants in the read few (read many) conditions received the following additional instruction:

Before moving on to the next section, please review the thoughts listed by another analyst about how future financial performance might not be as positive as Villa Fiore expects. In other words, this analyst considered how Villa Fiore's plans to increase sales and profitability might fail.

Each read condition participant was matched with at most one generate condition participant and was provided with the counter-explanations generated by their matched participant. Except for corrected typographical errors, the counter-explanations provided to read condition participants were identical to those typed by the participants who generated them.¹³

Dependent Measures

Consistent with Experiment 1, we calculate the primary dependent measures (forecast increases in EPS) by subtracting the current EPS (-\$0.08) from participants' revised EPS forecasts for both one (year 1) and two years ahead (year 2). We use participants' preliminary forecast increases as covariates in our analyses.

We use participants' responses to relevant post-experimental questions as manipulation checks. Several participants failed to respond to one or more questions. We base each analysis on the maximum number of useable responses.

no such relationship, five participants answered "yes" to this question. We retain these observations in the reported analyses, but all inferences are identical if data from these participants are excluded.

¹³ This matching procedure necessitated collecting data in stages. Our initial invitations to participate were distributed to a portion of the participants pre-assigned to the control and generate conditions, only. Subsequent invitations included all conditions.

Results

Preliminary Analyses

We exclude two participants' forecast increases in EPS from the data analyses because they differed from sample means by more than four standard deviations, and DFFITS and DFBETA procedures identify them as influential outliers. Reported analyses use the remaining 129 observations.

Manipulation Checks

Participants in the generate many condition were asked to list ten reasons why managers' plans might fail. Consistent with participants from the analogous condition in the Sanna et al. (2002) hindsight study, our participants listed between two and ten reasons, with a mean of 6.67 reasons. Although 19 of the 30 participants in the generate many condition did not list a full set of ten reasons, participants in this condition still listed significantly more counter-explanations than did participants in the generate few condition (means = 6.67 and 2.00 for the generate many and few conditions, respectively, $t_{29} = 8.59, p < 0.01$). Participants asked to generate ten counter-explanations also found the task more difficult than did those participants asked to generate two counter-explanations (means [standard deviations] are 4.70 [1.95] and 3.59 [1.87] for the generate many and generate few conditions, respectively; $t_{55} = 2.18, p = 0.02$).

Tests of Hypotheses

Table 2, Panel A reports adjusted means, standard deviations, and cell sizes for forecast increases in EPS for years 1 and 2 for Experiment 2. Table 2, Panel B reports results of the planned contrasts used to test our hypotheses. Our first two hypotheses replicate Experiment 1 results. Consistent with Hypothesis 1, participants asked to generate few counter-explanations made less optimistic EPS forecasts than did control condition participants ($t_{123} = 1.77, p = 0.04$,

and $t_{123} = 1.93, p = 0.03$ for year 1 and year 2, respectively). Consistent with Hypothesis 2, participants asked to generate many counter-explanations did not make less optimistic EPS forecasts than did control condition participants ($t_{123} = 1.22, p = 0.23$, two-tailed and $t_{123} = 1.33, p = 0.19$ for year 1 and year 2, respectively).¹⁴

Our second set of hypotheses predict that participants who read both few (Hypothesis 3) and many (Hypothesis 4) counter-explanations will make less optimistic earnings forecasts than will control condition participants. Both hypotheses are partially supported. Forecast increases in EPS for year 2 are less optimistic in both the read few ($t_{123} = 1.66, p = 0.05$) and read many ($t_{123} = 2.41, p = 0.01$) conditions than in the control condition. However, forecast increase in EPS for year 1 are not significantly less optimistic in the read few condition ($t_{123} = 1.21, p = 0.12$) and are only marginally less optimistic in the read many condition ($t_{123} = 1.50, p = 0.07$) than in the control condition.

Tests of Alternative Explanations

Consistent with Experiment 1 analyses, we perform tests to rule out potential alternative explanations for the results in Experiment 2.¹⁵ To ensure that the observed influence of our manipulations on forecast increases in EPS was not driven by differences in perceived accountability to either management or users of analysts' work across experimental conditions, we examine participants' ratings of the importance of providing favorable forecasts and the

¹⁴ We note that for year 2, the effect of generating many counter-explanations would be marginally significant were a one-tailed test employed.

¹⁵ Unlike the responses of Experiment 1 participants to the post-experimental questions asking participants to (1) identify the number of different ways that managers' plans might fail that they considered and (2) rate the amount of attention that they gave to each of the ways that managers' plans might fail, Experiment 2 participants' ratings vary with experimental condition. However, these ratings are unlikely to affect our hypothesis tests because the pattern of simple effects is inconsistent with our hypotheses. In both cases, when analyzed separately, the ratings of participants in the generate few and generate many conditions were marginally or significantly higher than those in the control condition, while the ratings of participants in the read conditions were not significantly different. Further, adding either rating as a covariate in our analyses does not change reported inferences.

importance of providing accurate forecasts (both measures elicited using 9-point scales). The importance of providing favorable forecasts does not vary with experimental condition ($F_{4,123} = 0.26, p = 0.91$). Although participants' ratings of the importance of providing favorable forecasts are positively associated with year 1 and year 2 forecast increases in EPS ($r = 0.20, p = 0.02$ for year 1 and $r = 0.18, p = 0.04$ for year 2), including the importance of providing favorable forecasts in the model as a covariate does not change reported inferences. Therefore, the importance of providing favorable forecasts is not driving reported results. Participants' ratings of the importance of giving accurate forecasts are not associated with either year 1 or year 2 forecast increases in EPS ($r = 0.01, p = 0.89$ and $r = -0.03, p = 0.73$, respectively).

We also examine whether characteristics of the participants could be causing observed differences across experimental conditions. We find that track within the MBA program (i.e., consulting, finance, marketing, strategy, other), total number of accounting classes, total number of finance classes, investment experience, and gender are all unrelated to the dependent measures (smallest $p = 0.197$).

Finally, results are likely not due to differences in the quality of counter-explanations generated between conditions. Participants in the read conditions are provided with counter-explanations identical to and in the same order as the counter-explanations listed by participants in the generate conditions. Thus, if the ineffectiveness of generating many counter-explanations (Hypothesis 2) is driven by recency or dilution effects, we should observe the same ineffectiveness when other participants read those many counter-explanations (Hypothesis 4). Instead, results show that reading many counter-explanations is effective in reducing unintentional optimism. Therefore, we do not believe that recency or dilution effects are driving our results.

V. CONCLUSION

This study investigates whether and how counter-explanation can be used to limit the unintentional forecast optimism induced by scenario thinking. We demonstrate that the debiasing influence of a counter-explanation task may be limited when the counter-explanation task itself is experienced as difficult by the decision maker. In our experiments, analysts and MBA students appear to use the ease or difficulty of generating counter-explanations (i.e., their availability) as a cue when making EPS forecasts for a firm reporting prior losses. Consistent with availability, participants who experience ease while generating few counter-explanations make annual EPS forecasts that are relatively less optimistic than the forecasts made by control condition participants. Participants who experience difficulty while generating many counter-explanations do not make relatively less optimistic annual EPS forecasts than do control condition participants even though experimental participants generate a large number of counter-explanations. In both experiments, we perform tests to rule out alternative explanations and thus, provide evidence that observed differences in the effectiveness of counter-explanation tasks for limiting the optimism induced by scenario thinking is driven by differences in availability. In Experiment 2, we provide additional evidence that results are not driven by variations in counter-explanation strength between experimental conditions because reading either few or many (equally available) counter-explanations reduces relative optimism, but only in two-year-ahead forecasts.

This study is the first that we know of to investigate whether and how counter-explanations reduce the unintentional optimism attributable to scenario thinking. We contribute to the literature in two ways. We extend Heiman (1990) by demonstrating that there are boundary conditions for the effectiveness of counter-explanation tasks in reducing cognitive

biases: the debiasing influence of counter-explanation tasks may be limited when the counter-explanation task itself is experienced as difficult by the decision maker. Additionally, we demonstrate that individuals use the experienced ease or difficulty of a counter-explanation task as a valid cue when completing a prediction task. Prior literature demonstrates the influence of such subjective accessibility experiences in traditional recall tasks in the context of thinking about known, mundane outcomes (e.g., the outcome of a football game). We show that subjective accessibility experiences also influence prediction tasks that require professional decision makers to assess the likelihood of future outcomes.

We conduct our study in a context in which unintentional optimism likely has implications for asset pricing: loss firms. Prior archival research shows that the incidence of firms reporting losses is high. For example, Hwang et al. (1996) report that approximately one-fourth of all companies reported losses (negative earnings) in at least one year over the prior two decades, and Butler and Saraoglu (1999) report that analysts overestimate actual earnings for loss firms approximately 72 percent of the time. In short, there is room for significant improvement in analysts' forecasts for firms reporting losses, and this study identifies a potential control procedure that can reduce decision error.

Our use of a hypothetical firm provides necessary control over the financial and background information provided to participants, but the absence of an earnings realization precludes us from calculating an absolute measure of forecast optimism. Still, because our study focuses on the *incremental* effect of using counter-explanation to reduce unintentional optimism in analysts' forecasts, we do not believe that our inferences are constrained by the use of a relative measure.

Optimism in analysts' long-term forecasts can be costly to both investors and to securities firms. Prior empirical research suggests that correcting for analysts' optimistic forecast errors can improve value estimates (Frankel and Lee 1998). Recently, a number of Wall Street firms agreed to a \$1.4 billion settlement for charges by the SEC, NASD, and NYSE, among others, that their analysts routinely issued overly optimistic stock research to investors in order to curry favor with corporate clients and to win investment banking business (Smith et al. 2003). Although these charges presumably relate to intentional analyst forecast optimism, addressing the more subtle sources of unintentional forecast optimism is likely to become of increasing concern to regulators, investors, and Wall Street analysts. Our study introduces theory-based, yet practical and cost-effective ways of reducing unintentional optimism in analysts' annual earnings forecasts: the generation of a small number of counter-explanations and the review of another analyst's counter-explanations.

REFERENCES

- Abarbanell, J. S., and V. L. Bernard. 1992. Tests of analysts' overreaction/underreaction to earnings information as an explanation for anomalous stock price behavior. *The Journal of Finance* 67 (3): 1181-1207.
- Abarbanell, J. S., and R. Lehavy. 2003. Can stock recommendations predict earnings management and analysts' earnings forecast errors? *Journal of Accounting Research* 41 (1): 1-31.
- Ackert, L. F., and G. Athanassakos. 1997. Prior uncertainty, analyst bias, and subsequent abnormal returns. *The Journal of Financial Research* 20 (2): 263-273.
- Affleck-Graves, J., L. R. Davis, and R. R. Mendenhall. 1990. Forecasts of earnings per share: Possible sources of analyst superiority and bias. *Contemporary Accounting Research* 6 (2): 501-517.
- Ali, A., A. Klein, and J. Rosenfeld. 1992. Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS. *The Accounting Review* 67 (1): 183-198.
- Ali, A., L. Hwang, and M. A. Trombley. 2003. Residual-income-based valuation predicts future stock returns: Evidence on mispricing vs. risk explanations. *The Accounting Review* 78 (2): 377-396.
- Arkes, H. R. 1991. Costs and benefits of judgment errors: Implications for debiasing. *Psychological Bulletin* 110 (3): 486-498.
- Bonner, S. E., R. Libby, and M. W. Nelson. 1996. Using decision aids to improve auditors' conditional probability judgments. *Accounting Review* 71(2): 221-240.
- Bradshaw, M.T., S. A. Richardson, and R. G. Sloan. 2003. Pump and dump: An empirical analysis of the relation between corporate financing activities and sell-side analyst research. Working paper, Harvard Business School, University of Pennsylvania, and University of Michigan.
- Bradshaw, M. T. 2004. How do analysts use their earnings forecasts in generating stock recommendations? *The Accounting Review* 79(1): 25-50.
- Brown, L. D. 1997. Analyst forecasting errors: Additional evidence. *Financial Analysts Journal* (November/December): 81-88.
- Brown, L., D. 2001. A temporal analysis of earnings surprises: Profits versus losses. *Journal of Accounting Research* 39 (2): 221-241.

- Butler, K. C., and H. Saraoglu. 1999. Improving analysts' negative earnings forecasts. *Financial Analysts Journal* (May/June): 48-56.
- Byrnes, N. 2003. Earnings guidance: Silence is golden. *Business Week* (May): 87.
- Chi, M. T. H., M. Bassok, M. Lewis, P. Reimann, and R. Glaser. 1989. Self-explanations: How students study and use examples in learning to solve problems. *Cognitive Science* 13: 145-182.
- Chi, M. T. H., N. De Leeuw, M.-H. Chiu, and C. LaVancher. 1994. Eliciting self-explanations improves understanding. *Cognitive Science* 18: 439-477.
- Damodaran, A. 1994. *Damodaran on Valuation: Security Analysis for Investment and Corporate Finance*. New York, NY: John Wiley & Sons, Inc.
- Damodaran, A. 2001. *The Dark Side of Valuation: Valuing Old Tech, New Tech, and New Economy Companies*. Upper Saddle River, NJ: Prentice-Hall, Inc.
- Darrough, M. N., and T. Russell. 2002. A positive model of earnings forecasts: Top down versus bottom up. *Journal of Business* 75 (1): 127-152.
- Dawes, R. M. 1988. *Rational Choice in an Uncertain World*. Orlando, FL: Harcourt Brace Jovanovich.
- DeBondt, W. F. M., and R. H. Thaler. 1990. Stock market volatility: Do security analysts overreact? *American Economic Review* 80 (2): 52-57.
- Dechow, P. M., A. P. Hutton, and R. G. Sloan. 1999. An empirical assessment of the residual income valuation model. *Journal of Accounting and Economics* 26: 1-34.
- Dechow, P. M., A. P. Hutton, and R. G. Sloan. 2000. The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings. *Contemporary Accounting Research* 17 (1): 1-32.
- Downen, R. J. 1996. Analyst reaction to negative earnings for large well-known firms. *The Journal of Portfolio Management* 23 (1): 49-55.
- Dugar, A., and S. Nathan. 1995. The effect of investment banking relationships on financial analysts' earnings forecasts and investment recommendations. *Contemporary Accounting Research* 12 (1): 131-160.
- Duru, A., and D. M. Reeb. 2002. International diversification and analysts' forecast accuracy and bias. *The Accounting Review* 77 (2): 415-433.

- Eames, M., S. M. Glover, and J. Kennedy. 2002. The association between trading recommendations and broker-analysts' earnings forecasts. *Journal of Accounting Research* 40 (1): 85-104.
- Eames, M., and S. M. Glover. 2003. Earnings predictability and the direction of analysts' earnings forecast errors. *The Accounting Review* 78 (3): 707-724.
- Einhorn, H., and R. Hogarth. 1986. Judging probable cause. *Psychological Review* 99: 3-19.
- Elgers, P. T., and M. H. Lo. 1994. Reductions in analysts' annual earnings forecast errors using information in prior earnings and security returns. *Journal of Accounting Research* 32 (2): 290-303.
- Francis, J., and D. Philbrick. 1993. Analysts' decisions as products of a multi-task environment. *Journal of Accounting Research* 31 (2): 216-230.
- Francis, J., J. D. Hanna, and D. R. Philbrick. 1997. Management communications with securities analysts. *Journal of Accounting and Economics* 24 (3): 363-394.
- Frankel, R., and C. M. C. Lee. 1998. Accounting valuation, market expectation, and cross-sectional stock returns. *Journal of Accounting and Economics* 25: 283-319.
- Graham, J. R., C. R. Harvey, and S. Rajgopal. 2004. The economic implications of corporate financial reporting. Working paper, Duke University, National Bureau of Economic Research, and University of Washington.
- Hawkins, S. A., and R. Hastie. 1990. Hindsight: Biased judgment of past events after the outcomes are known. *Psychological Bulletin* 107: 311-327.
- Heiman, V. B., 1990. Auditors' assessments of the likelihood of error explanations in analytical review. *The Accounting Review* 65 (4): 875-890.
- Hoch, S. J. 1984. Availability and interference in predictive judgment. *Journal of Experimental Psychology: Learning, Memory, and Cognition* 10 (4): 649-662.
- Huberts, L. C., and R. J. Fuller. 1995. Predictability bias in the U.S. equity market. *Financial Analysts Journal* (March/April): 12-28.
- Hunton, J. E., and R. A. McEwen. 1997. An assessment of the relation between analysts' earnings forecast accuracy, motivational incentives and cognitive information search strategy. *The Accounting Review* 72 (4): 497-515.
- Hwang, L., C. Jan, and S. Basu. 1996. Loss firms and analysts' earnings forecast errors. *The Journal of Financial Statement Analysis* (Winter): 18-30.

- Irvine, P., S. Nathan, and P. Simko. 1998. The relation between securities firms' mutual fund equity holdings and their analysts' earnings forecasts. Working paper, Emory University, Georgia State University, and Emory University.
- Irvine, P. 2004. Analysts' forecasts and brokerage-firm trading. *The Accounting Review* 79 (1): 125-149.
- Jacob, J., S. Rock, and D. P. Weber. 2003. Do analysts at independent research firms make better earnings forecasts? Working paper, University of Colorado at Boulder.
- Kahn, R. N., and A. Rudd. 1999. Modeling analyst behavior. *Journal of Investing* 8 (2): 7-14.
- Kahneman, D., and A. Tversky. 1982. The simulation heuristic. In *Judgment Under Uncertainty: Heuristics and Biases*, edited by D. Kahneman, P. Slovic, and A. Tversky. Cambridge, U.K.: Cambridge University Press.
- Kahneman, D., and D. Lovallo. 1993. Timid choices and bold forecasts: A cognitive perspective on risk taking. *Management Science* 39 (1): 17-31.
- Kennedy, J. 1993. Debiasing audit judgment with accountability: A framework and experimental results. *Journal of Accounting Research* (Autumn): 231-245.
- Kennedy, J. 1995. Debiasing the curse of knowledge in audit judgment. *The Accounting Review* 70 (2): 249-273.
- Kim, C., and S. Lustgarten. 1998. Broker-analysts' trade-boosting incentive and their earnings forecast bias. Working paper, Queens College of The City University of New York and Baruch College of The City University of New York.
- Klein, A. 1990. A direct test of the cognitive bias theory of share price reversals. *Journal of Accounting and Economics* 13: 155-166.
- Koehler, D. J. 1991. Explanation, imagination, and confidence in judgment. *Psychological Bulletin* 110 (3): 499-519.
- Koonce, L. 1992. Explanation and counterexplanation during audit analytical review. *The Accounting Review* 67 (1): 59-76.
- Krishnan, M., and K. Sivaramakrishnan. 1998. A theory of analyst forecast bias. Working paper, Rutgers University and Texas A&M University.
- Lee, C. M. C., J. Myers, and B. Swaminathan. 1999. What is the intrinsic value of the Dow? *The Journal of Finance*. 54 (5): 1693-1741.

- Levi, A. S., and J. B. Pryor. 1987. Use of the availability heuristic in probability estimates of future events: The effects of imagining outcomes versus imagining reasons. *Organizational Behavior and Human Decision Processes* 40: 219-234.
- Lim, T. 2001. Rationality and analysts' forecast bias. *The Journal of Finance* 56 (1): 369-385.
- Lin, H., and M. F. McNichols. 1998. Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics* 25: 101-127.
- Lipe, M. G. 1991. Counterfactual reasoning as a framework for attribution theories. *Psychological Bulletin* (May): 456-471.
- Liu, J., and J. Thomas. 2000. Stock returns and accounting earnings. *Journal of Accounting Research*. 38 (1): 71-101.
- Matsumoto, D. A. 2002. Management's incentive to avoid negative earnings surprises. *The Accounting Review* 77 (3): 483-514.
- McNamara, D. S. and A. F. Healy. 1995. A generation advantage for multiplication skill and nonword vocabulary acquisition. In A. F. Healy & L. E. Bourne, Jr. (Eds.), *Learning and memory of knowledge and skills: Durability and specificity* (pp. 132-169). Thousand Oaks, CA: Sage.
- McNichols, M., and P. C. O'Brien. 1997. Self-selection and analyst coverage. *Journal of Accounting Research* 35 (Supplement): 167-199.
- National Investor Relations Institute (NIRI). 2003. NIRI issues survey results on earnings guidance practices; First Call eliminates the term "consensus." *Executive Alert: Updates on Issues Vital to the Practice of Investor Relations*. Available on-line at: http://www.niri.org/irresource_pubs/alerts/ea20031210.pdf.
- Nelson's Directory of Investment Research* (2003). Port Chester, NY: W.R. Nelson & Co.
- Ohlson, J. A., and B. E. Juettner-Nauroth. 2000. Expected EPS and EPS growth as determinants of value. Working paper, New York University and Johannes Gutenberg-University.
- Peecher, M. E., and I. Solomon. 2001. Theory and experimentation in studies of audit judgments and decisions: Avoiding common research traps. *International Journal of Auditing* 5 (3): 193-203.
- Previts, G. J., R. J. Bricker, T. R. Robinson, and S. J. Young. 1994. A content analysis of sell-side financial analyst company reports. *Accounting Horizons* 8 (2): 55-70.
- Rajan, R., and H. Servaes. 1997. Analyst following of initial public offerings. *The Journal of Finance* 52 (2): 507-529.

- Richardson, S., S. H. Teoh, and P. Wysocki. 2002. The walkdown to beatable analyst forecasts: The role of equity issuance and insider trading incentives. Working paper, University of Pennsylvania, The Ohio State University, and Massachusetts Institute of Technology.
- Roese, N. J., and J. M. Olson. 1996. Counterfactuals, causal attributions, and the hindsight bias: A conceptual integration. *Journal of Experimental Social Psychology* 32: 197-227.
- Roese, N. J. 1997. Counterfactual thinking. *Psychological Bulletin* 121 (1): 133-148.
- Roese, N. J., and S. D. Maniar. 1997. Perceptions of purple: Counterfactual and hindsight judgments at Northwestern Wildcats football games. *Personality and Social Psychology Bulletin* 23 (12): 1245-1253.
- Sanna, L. J., N. Schwarz, and S. L. Stocker. 2002. When debiasing backfires: Accessible content and accessibility experiences in debiasing hindsight. *Journal of Experimental Psychology: Learning, Memory and Cognition* 28 (3): 497-502.
- Schwarz, N., H. Bless, F. Strack, G. Klumpp, H. Rittenauer-Schatka, and A. Simons. 1991. Ease of retrieval as information: Another look at the availability heuristic. *Journal of Personality and Social Psychology* 61 (2): 195-202.
- Schwarz, N. 1998. Accessible content and accessibility experiences: The interplay of declarative and experiential information in judgment. *Personality and Social Psychology Review* 2 (2): 87-99.
- Sedor, L. 2002. An explanation for unintentional optimism in analysts' earnings forecasts. *The Accounting Review* 77 (4): 731-753.
- Slamecka, N. and P. Graf. 1978. The generation effect: Delineation of a phenomenon. *Journal of Experimental Psychology: Human Learning and Memory* 4 (November): 592-604.
- Smith, R., S. Craig, and D. Solomon. 2003. Wall street firms settle charges over research in \$1.4 billion pact. *Wall Street Journal*, April 29.
- Sougiannis, T., and T. Yaekura. 2001. The accuracy and bias of equity values inferred from analysts' earnings forecasts. *Journal of Accounting, Auditing & Finance* 16 (4): 331-362.
- Tasker, S. 1998. Bridging the information gap: Quarterly conference calls as a medium for voluntary disclosure. *Review of Accounting Studies* 3 (1-2): 137-167.
- Tversky, A., and D. Kahneman. 1973. Availability: A heuristic for judging frequency and probability. *Cognitive Psychology* 5: 207-232.
- Waldmann, M. R. 2000. Competition among causes but not effects in predictive and diagnostic learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition* 26: 3-76.

Waldmann, M. R. 2001. Predictive versus diagnostic causal learning: Evidence from an overshadowing paradigm. *Psychonomic Bulletin & Review* 8: 600-608.

Wanke, M., H. Bless, and B. Biller. 1996. Subjective experience versus content of information in the construction of attitude judgments. *Personality and Social Psychology Bulletin* 22(11): 1105-1113.

Wall Street Journal. 2002. Coca-Cola to end practice of giving earnings forecasts. December 13.

TABLE 1
Experiment 1: Descriptive Statistics and Planned Contrasts Used to Test Hypotheses

Panel A. Descriptive Statistics

<i>Condition</i>	<i>Adjusted mean (standard deviation)</i>	
	<i>Year 1</i>	<i>Year 2</i>
Control (n = 17)	0.29 (0.19)	0.62 (0.26)
Generate Few (n = 24)	0.17 (0.19)	0.46 (0.26)
Generate Many (n = 15)	0.25 (0.19)	0.54 (0.26)

Panel B. Planned Contrast Tests of Hypotheses

<i>Hypothesis Contrast</i>	<i>p-value, Year 1</i>	<i>p-value, Year 2</i>
H1: Lower relative optimism for generate few versus control	0.02	0.03
H2: No difference in relative optimism for generate many versus control	0.50	0.35

Notes:

Panel A provides descriptive statistics by experimental condition. The dependent variable, forecast increase in EPS for year t , is defined as the revised forecast for year t – the most recent EPS value provided to participants (-\$.64) with $t = 1$ or 2 , adjusted for the influence of the preliminary (pre-manipulation) forecast using analysis of covariance (ANCOVA). Participants made preliminary EPS forecasts after reading summarized financial information and revised EPS forecasts after reading conference call excerpts (which present information about managers' plans to improve future earnings in scenario structure) and after generating counter-explanations (if applicable). Participants in the generate few (many) condition were asked to list two (twelve) reasons why managers' plans could fail before making revised forecasts. Participants in the control condition were not asked to generate counter-explanations before making revised forecasts.

Panel B provides tests of hypotheses comparing the forecasts of experimental participants to those of participants not asked to generate counter-explanations (i.e., control condition participants) to determine whether the effectiveness of counter-explanation at limiting unintentional optimism is moderated by the ease or difficulty experienced during the counter-explanation task. Forecast optimism is calculated by comparing forecast increases in EPS of experimental condition participants to forecast increases in EPS of control condition participants. If the forecast increases in EPS in experimental conditions are less than the forecast increases in EPS in the control condition, then experimental condition participants are *relatively less optimistic*.

P-values are one-tailed for the directional prediction in Hypothesis 1 and two-tailed for Hypothesis 2.

TABLE 2
Experiment 2: Descriptive Statistics and Planned Contrasts Used to Test Hypotheses

Panel A. Descriptive Statistics

<i>Condition</i>	<i>Adjusted mean (standard deviation)</i>	
	<i>Year 1</i>	<i>Year 2</i>
Control (n = 27)	0.16 (0.12)	0.27 (0.16)
Generate Few (n = 27)	0.11 (0.12)	0.18 (0.16)
Generate Many (n = 30)	0.13 (0.12)	0.21 (0.16)
Read Few (n = 23)	0.12 (0.12)	0.19 (0.16)
Read Many (n = 22)	0.11 (0.12)	0.16 (0.16)

Panel B. Planned Contrast Tests of Hypotheses

<i>Hypothesis Contrast</i>	<i>p-value, Year 1</i>	<i>p-value, Year 2</i>
H1: Lower relative optimism for generate few versus control	0.04	0.03
H2: No difference in relative optimism for generate many Versus control	0.23	0.19
H3: Lower relative optimism for read few versus control	0.11	0.05
H4: Lower relative optimism for read many versus control	0.07	0.01

Notes:

Panel A provides descriptive statistics by experimental condition. The dependent variable, forecast increase in EPS for year t , is defined as the revised forecast for year t – the most recent EPS value provided to participants (-\$.08) with $t = 1$ or 2, adjusted for the influence of the preliminary (pre-manipulation) forecast using analysis of covariance (ANCOVA). Participants made preliminary EPS forecasts after reading summarized financial information and revised EPS forecasts after reading conference call excerpts (which present information about managers' plans to improve future earnings in scenario structure) and after generating or reading counter-explanations (if applicable). Participants in the generate few (generate many) condition were asked to list two (ten) reasons why managers' plans might fail before making revised forecasts. Participants in the read few (read many) condition were asked to read the reasons why managers' plans might fail that were generated by a participant in the generate few (generate many) condition. Participants in the control condition were not asked to generate or read counter-explanations before making revised forecasts.

Panel B provides tests of hypotheses comparing the forecasts of experimental participants to those of participants not asked to generate or read counter-explanations (i.e., control condition participants) to determine (a) whether the effectiveness of counter-explanation at limiting unintentional optimism is moderated by the ease or difficulty experienced during the counter-explanation task (H1 and H2) and (b) whether the observed effect driven by variations in counter-explanation strength between experimental conditions (H3 and H4). Forecast optimism is calculated by comparing forecast increases in EPS of experimental condition participants to forecast increases in

EPS of control condition participants. If the forecast increases in EPS in experimental conditions are less than the forecast increases in EPS in the control condition, then experimental condition participants are *relatively less optimistic*.

P-values are one-tailed for directional predictions (Hypotheses 1, 3, and 4) and two-tailed for Hypothesis 2.

APPENDIX
Conference Call Excerpt - Experiment 1:
Managers' Plans to Improve Future Earnings

Villa Fiore hosted a conference call on July 19, 2003 following its earnings announcement for the fiscal year ended June 30, 2003.

The following is an excerpt from the remarks made by the Chief Executive Officer about Villa Fiore's plans and expectations for the upcoming fiscal year (year ending June 30, 2004) and beyond.

“Although we are pleased that our 2003 results represent increases over both 2001 and 2002, we are disappointed that we were unable to achieve profitability. However, we have aggressive plans to improve future financial performance, and I will share those plans with you during this portion of today's conference call.

As you may know, industry-wide premium wine sales have increased over the past few years and account for more than 60% of California's winery revenues. To improve our position in this intensely competitive market, we plan to increase the visibility and exposure of our wines. This upcoming year, for the first time, you will see our high-end premium wines featured in elaborate, full-page advertisements in important industry publications like *Wine Spectator*. Additionally, we will continue to expand our distribution channels to increase our wine's presence in restaurants and retail outlets nationally. This fall, our high-end premium wines will debut in several gourmet restaurants including Napa Valley's *French Laundry*, San Francisco's *Rubicon*, and New York's *Aquavit*.

In addition to enhancing the visibility of our high-end premium wines, we plan to broaden our market appeal by releasing a new product in fiscal year 2004...our Villa Fiore Red Table Wine. Recent data from supermarkets and other large-volume outlets indicates that U.S. produced table wine now represents more than 80% of the wine volume in those stores. With a suggested retail price of \$10 per bottle, releasing a table wine will allow us to increase sales dramatically by attracting new consumers with preferences for high-quality, value-priced red wines. Additionally, the vineyards we have scheduled to come into production in 2005 through 2008 will ensure that we can continue to improve over typical value-priced wines and to deliver excellent values to cost-conscious consumers in the future. To further ensure the success of our new product, we are negotiating with several potential strategic partners that specialize in the national marketing of value-priced premium wines.

In summary, we expect that the targeted marketing of our existing high-end premium wines, complemented by the introduction of our value-priced premium table wine, will allow us to capture a wider range of the growing consumer wine market and to increase our sales substantially. As a result, we plan to achieve profitability in the near term and to generate substantial profits in the long run...”