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Security analysts' investment recommendations

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SECURITY ANALYSTS' INVESTMENT RECOMMENDATIONS

A DISSERTATION
SUBMITTED TO THE GRADUATE SCHOOL OF BUSINESS
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OF STANFORD UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Hsiou-wei William Lin
May 1994

I certify that I have read this dissertation and that in my opinion it is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Maureen F. McNichols (Principal Adviser)

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Abstract

This dissertation explores the factors that influence analysts' recommendations and investor response to these signals. First, it examines how analysts' current and long-term earnings estimates for a company, the company's systematic risk, and its stock's prior performance influence their recommendations for that company. Investment recommendations can generally be characterized as relatively coarse and vague. However, the informativeness of recommendations, which defines analysts' roles as information intermediaries, corresponds to the extent recommendations are myopic, risk-adjusted and retrospective. Via ordered probit analyses, this dissertation provides evidence that (1) analysts' recommendations are not completely myopic, (2) recommendations are not fully adjusted for systematic risk, and (3) pre-recommendation abnormal returns significantly affect recommendation rankings.

Second, this dissertation examines market reactions to recommendations, investigating how these signals influence investors' beliefs. Bias in recommendations may arise from analysts' reliance on lines of communication with corporate executives and or pressure to curry favor with client companies. As mentioned above, analysts' recommendations may also be characterized as coarse and vague. To investigate whether these potential weaknesses make recommendations uninformative, as well as whether investors adjust their beliefs for analysts' strategic behavior, I conduct significance tests of abnormal returns and volume. The findings suggest that (1) recommendations are informative but upward-biased, (2) the impact on security returns is much stronger for recommendations than earnings forecast revisions, and (3) whereas investors adjust for expected recommendation bias, they appear to over-react (under-react) to favorable (unfavorable) recommendations upon their issuance.

Third, it examines analysts' forecasts and recommendations for public utilities, further investigating the extent strategic factors motivate analysts to deviate from issuing unbiased reports. Because regulators are likely to lower rates if earnings prospects are too high, utility executives may prefer to receive pessimistic earnings forecasts. These executives, nevertheless, may still prefer optimistic recommendations, since several characteristics of recommendations, including coarseness and vagueness, are likely to limit the amount of information regulators can extract from recommendations about analysts' profitability expectations. Consistently, by comparing (1) bias in earnings forecasts for utility versus non-utility firms, and (2) earnings forecasts and recommendations provided by underwriter versus non-underwriter analysts, I find evidence that conflicting pressure may result in pessimistic (optimistic) earnings forecasts (recommendations).

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Introduction

This dissertation examines the factors that influence analysts' investment recommendations and investor response to these signals. Security analysts have been regarded as an important sector in the system that produces and uses company-specific information. As stated in Beaver (1989),

> The information network among executives and analysts may be the mechanism which permits security prices to promptly reflect a comprehensive information system.

This mechanism consists of two stages. First, analysts incorporate market, industry, and firm-specific information into their firm value expectation, and base their investment recommendations, at least in part, on whether this suggests a firm's shares are under-valued or over-valued. Strategic factors may also motivate an analyst to deviate from issuing an unbiased recommendation. Second, investor response to analysts' research reports is reflected in stock price and volume changes.

Chapter 1 of this dissertation explores the extent non-strategic financial factors including an analyst's current and long-term earnings estimates for a company, the company's systematic risk, and its stock's prior-period price performance influence his recommendations for that company. Investment recommendations can generally be characterized as relatively coarse and vague, in that security analysts' research reports rarely specify analysts' risk assessments, investment horizons, or the extent the recommendations are retrospective. However, the informativeness of an analyst's recommendation, which defines the role of the analyst as an information intermediary, corresponds to the extent analysts adjust for the market risk, the extent analysts have longer-term perspectives, and the extent prior-period price changes affect the recommendation decisions. In order to measure the significance of these factors, I estimate ordered probit models via maximum likelihood methods. The test results indicate that (1) security analysts' recommendations are not completely myopic, (2) analysts' recommendations are not fully adjusted for systematic risk, and (3) pre-recommendation abnormal returns significantly affect recommendations.

Focusing on market response to investment recommendations and earnings forecast revisions, Chapter 2 investigates how these signals influence investors' beliefs. As primary providers of competing information to companies' financial reports and disclosures, sell-side analysts may encounter substantial endeavors from corporate executives who want a favorable report. Bias in analysts' prospective reports may arise from analysts' reliance on lines of communication with corporate executives. Moreover, brokerage analysts, whose research reports are often part of a group of bundled services offered by full-service investment banking firms, may have incentives to curry favor with client companies. Investment recommendations, as the most direct signal for security analysts' anticipated changes in firm values, should reflect strategic behavior most evidently. In addition to the potential for bias, the coarseness and vagueness of analysts' recommendations may make recommendations less informative. To investigate the implications of these effects for the informativeness of analysts' recommendations, as well as the extent to which investors adjust their beliefs for analysts' strategic behavior, this study examines investor response to recommendations as reflected in abnormal returns and volume. The findings suggest that (1) recommendations are informative but upward biased, (2) the impact on security returns is much stronger for recommendations than earnings forecast revisions, and (3) whereas the investing public appear to adjust for expected bias in recommendations, they appear to over-react (under-react) to favorable (unfavorable) recommendations upon their issuance.

Chapter 3 of this dissertation examines analysts' forecasts and recommendations for public utility firms, further investigating the extent conflicting pressure explains the variation in analysts' research reports. A maintained hypothesis of this study is that regulators are likely to lower rates if earnings prospects are too high. If so, then executives of utility firms may prefer that security analysts issue pessimistic earnings forecasts. These executives, nevertheless, may still prefer optimistic recommendations. Although favorable recommendations are also observable to regulators, the coarseness and vagueness of recommendations are likely to limit the amount of information regulators may extract from them. As a consequence, conflicting pressure may result in analysts' biasing down their earnings forecasts without biasing down contemporaneous recommendations. Consistently, my comparison test results indicate that (1) security analysts' earnings forecasts for utility (non-utility) firms are less (more) optimistic, (2) underwriter analysts bias their investment recommendations (earnings forecasts) upwards (downwards) for utility firms, and (3) the differences between underwriter analysts' and comparison analysts' five-year growth estimates for utilities become more pronounced as the underwriter analysts' growth estimates become greater. This direction of bias contrasts with systematic optimism in both earnings forecasts and recommendations as documented by prior studies focusing on industrial firms.

These questions are of interest to accounting researchers for several reasons. First, this study contributes to our understanding of the characteristics of analysts' recommendations. As Schipper (1991) suggests, the focus of accounting research on analysts' earnings forecasts has ignored how earnings forecasts relate to the other responsibilities of financial analysts. In this regard, the finding of this thesis that investment recommendations play a greater role in explaining revisions of investor beliefs than do earnings forecast revisions suggests researchers may be overestimating the appropriateness of using analysts' earnings forecasts as proxies for investor expectations. Second, this study provides a systematic and broad-based investigation of strategic behavior by security analysts. Investment recommendations, as the most direct signal for security analysts' anticipated changes in firm values, should reflect analysts' strategic behavior and investors' adjusting for research report bias most evidently. Specifically, it documents that the distribution of investment recommendations is not symmetric, with a striking tendency toward *buy* recommendations rather than *hold* or *sell* recommendations. This may reflect bias in recommendations or a tendency to issue recommendations only when they are favorable. Tests of security market reactions provide evidence that investors perceive recommendations to be biased upward, and that they adjust their expectations accordingly. Third, investigations of security market behavior associated with analyst recommendations demonstrate the feasibility of adopting these measures to examine the *importance* and *timeliness* of information in accounting signals. As Chapter 1 proposes, analyst recommendations can complement abnormal returns in exploring how accounting signals convey information to the market or reflect factors affecting stock prices. This potential warrants a thorough examination of analyst recommendations, including their information content and bias. Fourth, by documenting post-recommendation announcement drifts as well as exploring whether investors' perceptions of their information providers and securities' transaction properties account for the systematic post-recommendation abnormal returns, this study adds to the contemporary literature of market irregularities. Fifth, demonstrating that the potential for regulatory intervention may result in bias in analyst research reports expands our understanding of the forces that contribute to bias in analysts' earnings forecasts and recommendations.

Chapter 1: An Investigation of Factors that Influence Security Analysts' Investment Recommendations

Abstract

The objective of this chapter is to investigate how a security analyst's earnings per share (EPS) forecast revisions and long-term growth estimates for a company, the company's systematic risk, and its stock's pre-recommendation abnormal returns are related to the analyst's investment recommendation for that company. Analysts' recommendations can generally be characterized as relatively coarse and vague. In particular, security analysts' research reports rarely specify analysts' risk assessments, investment horizons, and the extent the recommendations are retrospective. However, the informativeness of an analyst's recommendation corresponds to the extent analysts adjust for the market risk, the extent analysts have longer-term perspectives, and the extent prior-period price changes affect the ranking decisions. In order to measure the significance of these factors, I estimate ordered probit models via maximum likelihood methods. The test results are consistent with the hypotheses that (1) security analysts' recommendations are not completely myopic, (2) analysts' recommendations, however, are not fully adjusted for systematic risk, and (3) pre-recommendation abnormal returns significantly affect investment recommendations. These results add to researchers' understanding of analysts' roles as users and producers of firm-specific information. They also provide motivation and empirical grounds for studies in the next two chapters of this dissertation.

1. Introduction/Literature Review

This study investigates (1) how security analysts associate their firm value expectation of a company with the expected changes of its future earnings, (2) whether analysts fully adjust for systematic risk when making recommendations, and (3) how pre-recommendation price performance affects analyst recommendations. Security analysts generally rank the equity securities in their universe with *strong buy, buy, hold, hold/sell,* or *strong sell* based on their price performance predictions.[1] Analysts' research reports may be the major competing signal to companies' financial reports/disclosures. The informativeness of these signals, and thus the extent they can influence investors' beliefs, depend in part on the extent analysts adjust for the market risk, the extent analysts have longer-term perspectives, and the extent prior-period price performance affects the ranking decisions. However, coarseness and vagueness are distinctive characteristics of analysts' recommendation reports. Security analysts' research reports rarely specify their risk assessments, investment horizons, or the extent the recommendations are retrospective. Nor does there exist any prior accounting or finance research that investigates the association between recommendations and these factors.

Aiming to explore the potential non-strategic inputs in analysts' ranking decision process, I conduct both single- and multiple-factor ordered probit analyses to measure the significance of the above three factors. First, this study examines the relative importance of analyst current-year earnings forecast revisions, and two proxy variables of longer-term earnings expectation, two-year-ahead earnings forecast (Fy2) revisions, and five-year EPS growth estimate, exploring whether analysts have longer-term perspectives. Prior research has argued that investors and executives do not pay sufficient attention to companies' longer-term profitability.[2] Security analysts' recommendation ratings, as a major reference signal for investors' buying and selling the stocks, are likely to correspond with the extent investors are myopic. Second, this study examines the extent security analysts take into

1 Some information intermediaries adopt numerical ranking systems. Also, some agencies use different terminology. Consistent with the categories adopted in Research Holdings Limited Database, the data source of recommendations for this study, this study adopts these representative rankings.

2 Onkvisit and Shaw (1991), who explore factors that contribute to U.S. firms' lack of strength of competitiveness, criticize that U.S. executives want a quick return whereas their Japanese counterparts are more concerned with long-term vitality. Also, Dobrzynski, Shiller, Miles, Norman and King (1986) report that business leaders encounter intense pressure for current earnings. Moreover, analytical work by Stein (1989) shows that if the market (1) conjectures no myopia, and (2) uses current earnings to make a rational forecast of firm value, in equilibrium managers will have an incentive to boost their current earnings.

account systematic risk while revising their investment blueprints, so investors with risk tolerance levels different from the analysts' can interpret the recommendation appropriately. Accounting researchers have limited understanding as to whether recommendations are fully adjusted for the market risk. Despite the prevalence of the Capital Asset Pricing Model (CAPM) in market-based research studies, there are anecdotes that suggest non-trivial inconsistency in interpreting investment recommendations between researchers and practitioners. Third, this study explores whether pre-recommendation abnormal returns affect analysts' ranking decisions. Above all, security analysts use "action verbs" for the ratings. To naive investors, a *buy* (*sell*) recommendation seems to signal an anticipated future increase (decrease) in security price. Moreover, there are anecdotes that investment recommendations directly disclose an analyst's prediction regarding future price performance of a security to investors.

The results of this study are consistent with the notion that analysts recommend more favorably for firms for which they provide greater current- or subsequent-year earnings forecasts revisions or greater five-year earnings per share growth estimates, for firms with greater systematic risk, and for firms with greater pre-recommendation abnormal returns.

The next section consists of a discussion of the institutional background and hypotheses of this study. Section 3 briefly introduces ordered probit, an analytical tool for linear models with discrete dependent variables. Section 4 describes the data. Section 5 explores whether security analysts have longer-term perspectives. Section 6 investigates whether analysts fully adjust for the market risk when making recommendations. Section 7 explores whether analyst recommendation ratings correspond to pre-recommendation price performance. Section 8 conducts multiple-factor ordered probit analyses, providing evidence on incremental explanatory power of each potential factor. Finally, Section 9 concludes the study and discusses potential future areas of work.

2. Institutional Background and Hypotheses

2.1. ANALYSTS' INVESTMENT HORIZONS

This study first investigates how analysts weigh their one-year-ahead earnings forecast revision (*FY1REV*), two-year-ahead earnings forecast revision (*FY2REV*), and five-year EPS growth estimate (*GROWTH*) when making recommendations. Most security analysts assert that they aim to serve investors with long-term investment horizons. In a survey I conducted in June 1992 (hereafter the *Survey*), in which each of 130 randomly selected security analysts was sent a questionnaire, the subjects were asked how their earnings forecasts and recommendations were made.[3] As the analysts were requested to indicate the relative importance of potential variables for their forming or changing recommendations on a company's shares, most of them stated that the current share price, FY1, FY2, and growth rate are the major factors that influence their recommendation ratings.[4] The validity of this assertion has non-trivial implications. Prior research has argued that investors and executives do not pay sufficient attention to companies' longer-term profitability. Security analysts' recommendation ratings, as a major reference signal for investors' buying and selling the stocks, are likely to correspond with the extent investors are myopic.[5]

To explore how analysts weigh information relevant to various horizons, I test the following hypotheses:[6]

$\mathbf{H_{1a}}$: Security analysts' investment recommendations are more favorable the greater their contemporaneous Fy1 EPS forecast revisions.

$\mathbf{H_{1b}}$: Security analysts' investment recommendations are more favorable the greater their contemporaneous Fy2 EPS forecast revisions when the effect of analysts' Fy1 forecast revisions is controlled.

$\mathbf{H_{1c}}$: Security analysts' investment recommendations are more favorable the greater their contemporaneous five-year EPS growth rate estimates when the effect of analysts' Fy1 forecast revisions is controlled.

2.2 SYSTEMATIC RISK

The informativeness of analyst recommendations, as well as the implication of these signals to investors, also depends on the extent analysts adjust for systematic risk when making recommendations. If the ratings are risk-adjusted, investors trading on analyst investment opinions could buy (sell) the securities receiving a *strong buy* (*strong sell*) and buffer against market index movement by short selling (investing the proceeds on) Standard and Poor's 500 Index Fund. If analysts do not adjust for systematic risk, investors who exclusively trade on the investment opinions could, say, simultaneously buy

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[3] Forty-three of these analysts answered and returned the survey.

[4] Appendix 1 presents questions and results of the *Survey*.

[5] Contributions of this investigation reach beyond providing evidence as to whether analyst recommendations appear to be non-myopic. It also shows what role accounting measures play in explaining changes of firm values.

[6] I state all hypotheses in this study in alternative form.

(sell) the securities that receive a *strong buy* (*strong sell*) and sell their (invest the proceeds on) treasury bills. On the one hand, given the sentiment that analyst recommendations are presented as finished goods of the rating process, it seems intuitive that these signals are market-model-beta adjusted. Otherwise, it would be difficult for investors with different levels of risk tolerance to interpret these signals. For example, a *buy* would have different information implications for investors who are more rather than less risk averse.

On the other hand by providing recommendations with a focus on future raw (unadjusted) returns, analysts could differentiate themselves with their expertise in timing the market as opposed to selecting the stocks. Despite the prevalence of Capital Asset Pricing Model (CAPM) in market-based research studies, there have been many practitioners who challenge investment strategies based on CAPM. This phenomenon is also consistent with the result of the *Survey*, in which only 20% of the analyst subjects stated that they take into account the risk factor to make a recommendation. In contrast, 37.5% of these analysts said that they give a *buy* rating when they expect a stock to have greater than average returns; 27.5% of them stated that they issue a *buy* recommendation when a company's share price is expected to increase in the near future.

To explore the extent analysts take systematic risk into account when revising their investment blueprints, I test the following hypothesis:

H_2: Analysts recommend more favorably for securities with greater market-model beta.

2.3 PRE-RECOMMENDATION PRICE MOVEMENT

This study explores pre-recommendation abnormal price changes as the third potential factor. On the one hand, for two reasons, I expect that an analyst's recommendation directly discloses an analyst's prediction regarding future returns of a security to investors. First, security analysts use "action verbs" for the ratings. To naive investors, a *buy* (*sell*) recommendation appears to signal a anticipated future increase (decrease) in security price. Second, in the *Survey*, every analyst participant stated that (1) the current share price is among the major factors that influence his recommendation ratings, and (2) a *buy* is issued when he expect a favorable price performance subsequent to the recommendation date. In this sense, if an analyst perceives the market as being informationally efficient and sufficiently liquid, his recommendations should be independent of the security's prior-period price changes. On the other hand, accounting researchers have limited understanding of the extent security analysts serve as forecasters of financial prospects as opposed to reporters of the past performance.[7] There exists no evidence as to whether and to what extent future prospects already reflected in the current price level affect analyst recommendations.

To investigate whether pre-recommendation abnormal returns affect analysts' ranking decisions, I test the following hypothesis:

H_3: Analysts make more favorable recommendations for securities with greater pre-recommendation abnormal returns.

3. The Ordered Probit Model

I use ordered probit methods to examine whether the above factors influence security analysts' recommendations.[8] Essentially, underlying the analyses is a linear model with an unobserved *continuous* dependent variable Ω, which denotes analysts' perceived attractiveness of the stock. The conditional mean of Ω is hypothesized as a linear function of factors such as earnings forecast revisions (*FY1REV* and *FY2REV*), pre-recommendation beta (*BETA*), and pre-recommendation price changes (*PRECAR*):

$$\Omega_{it} = \Theta_0 + \Theta_1\, FY1REV_{it} + \Theta_2\, FY2REV_{it} + \Theta_3\, BETA_{it} + \Theta_4\, PRECAR_{it} + \varepsilon_{it}$$

The unobservable underlying variable Ω corresponds to an observable variable *REC*, the level of analyst recommendation. *REC* can be viewed as an indicator function for Ω over five exhaustive and mutually exclusive regions of the state space:

$$\begin{array}{llcccc}
REC = & \textit{strong sell} & \Leftrightarrow & -\infty & < \Omega & < \lambda_{HS}, \\
REC = & \textit{hold sell} & \Leftrightarrow & \lambda_{HS} & \leq \Omega & < \lambda_{H}, \\
REC = & \textit{hold} & \Leftrightarrow & \lambda_{H} & \leq \Omega & < \lambda_{B}, \\
REC = & \textit{buy} & \Leftrightarrow & \lambda_{B} & \leq \Omega & < \lambda_{SB}, \\
REC = & \textit{strong buy} & \Leftrightarrow & \lambda_{SB} & \leq \Omega & < \infty.
\end{array}$$

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[7] See Beaver (1989).

[8] Ordered probit analysis can be viewed as a generalization of the linear regression model to cases where the dependent variable may be discrete. For further discussions regarding this specification, see Gurland, Lee and Dahm(1960), Berndt, Hall, Hall and Hausman (1974) and Hausman, Lo and MacKinlay (1992).

Adopting Maximum Likelihood Methods, I conduct ordered probit analyses to estimate the slope coefficients Θ_0, Θ_1, Θ_2, Θ_3, and Θ_4 of the unobserved linear model.[9]

For tests in this study, the specification of ordered probit outperforms the competing regression models. Above all, the conventional OLS models assume that the dependent variable is continuous, whereas ordered probit is a statistical tool for discrete dependent variables. Also, OLS regression models, which assume the same coefficient for each dependent versus independent variable mapping, produce heteroscedastic regression errors with categorical dependent variable.[10] This limitation would lead to inefficiency in slope coefficient estimates and unreliability in the normal significance levels associated with the test statistics. Furthermore, OLS constrains all category boundaries, λ_{HS}, λ_H, λ_B and λ_{SB} to be equally spaced. Namely, it assumes $\lambda_{HS} - \lambda_H = \lambda_H - \lambda_B = \lambda_B - \lambda_{SB}$. However, it is not clear whether the difference in the underlying attractiveness between, say, *strong buy* and *hold* may not be exactly twice as much as the difference between *sell* and *strong sell.* In addition, OLS constrains the state probabilities to be linear in the explanatory variable(s). The adversarial effect of this constraint is non-trivial. Note that the samples consist of a disproportionately large (small) number of *favorable* (*unfavorable*) recommendations. In contrast, ordered probit model allows for nonlinear effects by letting the data determine the category boundaries. Finally, tests in this study are not subject to the problem that probit model may be unreliable for tests with small sample size. With the number of observations ranging from 259 to 15,087, the ordered probit specification generates maximum likelihood estimates that can be analyzed reliably by asymptotic methods.[11]

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9 Ordered probit analysis estimates slope coefficients and the boundaries, λ_{HS}, λ_H, λ_B, and λ_{SB}, simultaneously.

10 For tests in this study, the underlying partitioning boundaries for securities' attractiveness are likely to be unequally spaced. Most evidently, for observations in the two extreme partitions, *strong buy* and *strong sell*, the within-category differences in explanatory variable measures of, say, Fy1 and Fy2 EPS forecast revisions, may be large relative to the inter-category differences in Fy1 or Fy2 forecast revisions.

11 See Davidson and MacKinnon (1984), who show that probit models may not be a reliable specification for tests with small sample size.

4. Data Description

4.1 ANALYSTS' FORECASTS AND RECOMMENDATIONS

One special feature of this study is its data on analyst earnings forecasts, growth estimates and recommendations (names of forecasting agencies and analysts, earnings estimates, five-year EPS growth estimates, recommendation ratings, and estimate/recommendation dates) from a large database. The database, which is provided by Research Holdings Limited Inc., contains all EPS forecasts and recommendations made between July 1987 and July 1993 by sell-side analysts employed at two hundred and seventy-two dealer/broker firms or advisory service agencies. The list of forecast and recommendation providers includes the major current information intermediaries as well as research agencies that have been merged or liquidated.

Table 1 presents analyst coverage information. The sample includes two test groups, *S & P 500 firms* and 540 *Non-S & P firms* randomly selected from the set of all 1992 COMPUSTAT companies.[12] For *S & P 500 firms* (*Non-S & P firms*), 15449 (3446) research reports are with both current-year EPS forecasts and recommendation ratings available in the database.

4.2 SPLIT AND RETURN DATA

This study collects data items including distribution factors and split dates for events such as stock split and stock dividends, closing prices, dividend-adjusted returns, and market return indices from the CRSP Daily Tape.

[12] *S & P 500 Firms* (*Non-S&P Firms*) serve as representatives of large (small) companies listed at NYSE, AMEX, and NASDAQ. The following table indicates there exist significant differences in company size between these two groups as of the end of 1992 fiscal year. (I obtain data for the first variable, total assets, from COMPUSTAT. The second variable, market value, is computed by multiplying year end close price to number of outstanding shares. The 1992 CRSP tape provides both price and share number data items.)

Test	Total Assets			Market Values		
Group	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
S&P 500	13,666	4,190	28,676	6,136	3,057	9,943
Non-S&P	657	114	4,167	487	93	1,852

5. Contemporaneous Analysts' Earnings Forecast Revisions and Long-Term Growth Estimates

5.1 RESEARCH DESIGN

This section explores whether analyst recommendations appear to be non-myopic. To empirically test the validity of the assertion that measures of longer-term earnings expectation are related to analyst recommendations, this study investigates how analysts weigh their earnings forecast revisions and EPS growth estimates.[13] I estimate the following ordered probit models:

$$REC = \alpha_0 + \alpha_1 \, FY1REV + \varepsilon_1 \quad (1)$$

$$REC = \beta_0 + \beta_1 \, FY2REV + \varepsilon_2 \quad (2)$$

$$REC = \gamma_0 + \gamma_1 \, GROWTH + \varepsilon_3 \quad (3)$$

$$REC = \pi_0 + \pi_1 \, FY1REV + \pi_2 \, FY2REV + \varepsilon_4 \quad (4)$$

where *REC* denotes the level of analyst recommendations; *FY1REV* (*FY2REV*) is defined as relative change in current-year (subsequent-) EPS forecast deflated by close price at trading day -61, where day 0 is the recommendation date. Also, *GROWTH* denotes contemporaneous five-year EPS growth estimate. This study adopts both Fy2 revision and EPS growth estimate as proxies for longer-term earnings expectations. The asymptotic standard covariance matrix of the parameter estimates are computed as the negative inverse of the matrix of first derivatives of the log-likelihood function with respect to the parameters (BHHH algorithm).[14] By examining t-statistics for estimates of the slope coefficients for the factors, I explore the extent to which analysts' recommendations correspond to their contemporaneous revisions of the short-term and longer-term prospective expectations.

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13 A subsequent test investigating whether investors are more or less myopic than security analysts utilizes the market price reactions to analyst forecasts to estimate investors' weights on companies' long-term prosperity measures. It then compares these estimates with those of the analysts.

14 All of the tables in this study exclusively report results of the tests adopting BHHH algorithm. However, in each and every ordered probit test, the results are also robust to specification checks with respect to the algorithm of estimating standard errors. For tests in Sections 5.1, 6.1, 7.1, and 8.1, I also derive standard errors either from analytic second derivatives (Newton) or from analytic first and second derivatives (Eicker-White). These sensitivity analysis results, which are similar to the ones adopting BHHH method, are available upon request.

5.2 EMPIRICAL RESULTS

Table 5 demonstrates evidence consistent with the notion that analysts place greater weight on their longer-term expectations. First, Panels A, B, and C show that analyst Fy1 forecast revisions, Fy2 forecast revisions, and five-year growth estimates all serve as important variables to analyst recommendations. Second, Panel D reports that when the effect of Fy1 revisions is controlled, analyst recommendations appear to change significantly with their Fy2 revisions. The finding reaffirms the survey result that analysts consider the companies' current and future accounting earnings as important factors that influence analyst recommendations.

6. Systematic Risk

6.1 RESEARCH DESIGN

This section explores whether analysts' *buy* (*sell*) recommendations imply positive (negative) market-model-beta-adjusted returns as opposed to positive (negative) cumulative raw returns. It presents how analysts, as representatives of sophisticated financial information users, adjust for risk while revising their beliefs on firm values. It also contributes to the financial market research by sorting out competing interpretations to analyst recommendation ratings, showing how investors should form their investment strategies based on these rankings. Ostensibly, recommendations, as finished goods of the rating process, should be fully adjusted for market risk, so that investors with risk tolerance levels different from an analyst's can appropriately interpret the recommendation. However, as noted earlier, many practitioners have challenged investment strategies based on CAPM. To empirically test whether the difference in systematic risk levels helps explain the variation in analyst recommendations, this study applies ordered-probit analysis of recommendation versus *BETA* and examines the slope coefficient estimate via the following model:

$$REC = \delta_0 + \delta_1 \, BETA + \varepsilon_5 \qquad (5)$$

where *REC* denotes the level of analyst recommendations. *BETA* denotes the slope coefficient estimate of the market model with pre-recommendation estimation period [-292,-42], where trading day 0 is the recommendation date.[15]

15 In subsequent tests, I also examine whether the market adjusts for risk while responding to analysts' recommendations.

6.2 EMPIRICAL RESULTS

Table 6 provides evidence that analysts make more favorable recommendations for securities with greater systematic risk. The slope coefficient for the market-model beta is significantly negative in every ordered probit test. The test result is consistent with the notion that analysts do not fully adjust for market risks when they issue the recommendations. This finding also reaffirms the result of the *Survey,* in which only 20% of the analyst participants stated that they adjust for risk in making recommendations.

7. Pre-Recommendation Abnormal Price Performance

7.1 RESEARCH DESIGN

To investigating the influence of pre-recommendation returns on recommendations, I estimate the following ordered probit models:

$$REC = \varphi_0 + \varphi_1\, CARN10 + \varepsilon_6 \qquad (6)$$

$$REC = \eta_0 + \eta_1\, CARN25 + \varepsilon_7 \qquad (7)$$

$$REC = \theta_0 + \theta_1\, CARN60 + \varepsilon_8 \qquad (8)$$

where *REC* denotes the level of analyst recommendations. *CARN10* denotes the cumulative abnormal returns during the period [-10, -1]. For specification checks, I also adopt twenty-five- and sixty-trading-day-cumulative returns, *CARN25* and *CARN60,* which respectively denote the cumulative abnormal returns during the period *[-25,-1]* and the cumulative abnormal returns during [-60, -1].

7.2 EMPIRICAL RESULTS

Table 4 reports that analysts appear to make more favorable recommendations for securities with greater pre-recommendation excess returns. Panel A shows that, for the *S & P 500* test group, the maximum likelihood coefficient estimates of the ordered probit model for beta-adjusted returns cumulated from day -60 to day -1 (day -10 to day -1) are significantly negative for all the years throughout the 1987-92 period (in five out of the six years examined). Consistently, Panel B shows that, for the *Non-S&P* test group, the coefficients for excess returns are significantly negative for both [-60,-1] and [-10,-1] intervals.

This finding adds to our understanding of analysts' ranking behavior and helps discriminate among three conflicting hypotheses of the correlation between prior-period security returns and analyst recommendations. First, analysts perceive a systematically positive correlation between prior-period and future security returns.[16] Thus analysts issue more favorable recommendations for securities with greater prior returns. This return-recommendation correlation hypothesis implies that analyst recommendations are, at least in part, retrospective as of the research report dates.[17] Second, analysts perceive no correlation between prior returns and future returns. Namely, analysts perceive the market to be informationally efficient and expect no correlation between the pre-recommendation returns and future price performance. This hypothesis also has the backing of weak-form EMH. However, it differs from the positive correlation hypothesis by recognizing analysts' perceived superior access to firm-specific information and analysts' concerns about their reputation.[18] Unlike analyst EPS forecasts, of which forecast accuracy may be improved by extracting information from prior security returns, analyst recommendations would appear to lack timeliness if there were *systematically* strong positive correlation between suggested price changes and pre-recommendation security returns.[19] After all, analysts are evaluated by the *post*-recommendation price performance. In an informationally efficient market, there should be no significant correlation between the prior-period returns and the recommendation. Third, security analysts perceive future returns to be negatively correlated with pre-recommendation returns. They believe that the market over-reacts to signals and thus make recommendations based on contrarian logic. There is some anecdotal evidence that, in their research reports, analysts sometimes advocate the rating opinions by arguing the companies' P/E ratios being high (low) relative to the prior levels. *Ex ante*, each of these hypotheses could be mapped to a specific view of financial statement users' trading behavior for support.

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16 One potential explanation to this phenomenon is financial information users' herding behavior.

17 By labeling these recommendations as showing lack of timeliness, this study does not intend to assert that analysts are incompetent. Untimely recommendations exist either when the rankings are retrospective or when the research findings are disseminated to close clients before being made public.

18 This hypothesis does not necessarily imply that analyst recommendations have information content. It does not exclude the possibility that all analysts are self-confident and provide non-retrospective, non-contrarian, but inaccurate investment advice.

19 Brown, Foster and Noreen (1985) document that no more than ten percent of the variance in analyst forecast revisions could be explained by prior security returns.

8. Multiple-Factor Ordered Probit Analyses

To explore whether Fyl/Fy2 earnings forecast revisions, market risk, and pre-recommendation returns each have incremental explanatory power for the variation of analyst recommendations, this section estimates the following ordered probit models:

$$REC = \zeta_0 + \zeta_1\ FY1REV + \zeta_2\ FY2REV + \zeta_3\ BETA + \zeta_4\ CARN60 + \varepsilon_9 \quad (9)$$
$$REC = \xi_0 + \xi_1\ FY1REV + \xi_2\ FY2REV + \xi_3\ BETA + \xi_4\ CARN25 + \varepsilon_{10} \quad (10)$$
$$REC = \sigma_0 + \sigma_1\ FY1REV + \sigma_2\ FY2REV + \sigma_3\ BETA + \sigma_4\ CARN10 + \varepsilon_{11} \quad (11).$$

Table 5 presents the result of multiple-factor ordered probit analyses. Panel A reports the result of the test including analyst's revision of current-year EPS forecast revision (FY1REV) as an explanatory variable along with pre-recommendation betas and pre-recommendation cumulative excess returns. It shows that when the effect of pre-recommendation beta (BETA) and pre-recommendation abnormal returns is controlled, FY1REV appears to have no significant power in explaining the variation of contemporary analyst recommendation. In contrast, Panel B reports that when the effect of BETA and pre-recommendation abnormal returns is controlled, FY2REV appears to be a consistently significant factor in the contemporary recommendation. Consistently, Panel C shows that when FY1REV and FY2REV both serve as explanatory variables in the multiple-factor ordered probit model, FY1REV (FY2REV) appears to have trivial (significant) explanatory power for recommendations. The finding that Fy2 outperforms Fyl in conveying incremental information for both *S & P 500* and *Non-S&P firms* indicates that security analysts do not have an exclusively short-term perspective. It is also consistent with the notion that Fy2 reflects relatively more (less) of the permanent (transitory) component of earnings.[20]

9. Discussion and Extension

This study estimates the ordered probit models via maximum likelihood and uses the parameter estimates to measure the empirical significance of potential non-strategic inputs in analysts' decision process. The test results are consistent with the hypotheses that (1) security analysts' recommendations are not completely myopic, (2) analysts'

20 Brown, Foster and Noreen (1985) suggest that analyst one-year-ahead forecasts may have a higher transitory earnings component than two-year-ahead forecasts. Also, security analysts may consciously tailor their current-year forecasts to the GAAP-base numbers to be reported by the company but use the two-year-ahead forecasts to convey their expectation about permanent earnings.

recommendations, however, are not fully adjusted for systematic risk, and (3) pre-recommendation abnormal returns significantly affect recommendation rankings. These results add to accounting researchers' understanding of analysts' roles as users and producers of firm-specific information. They also provide motivation and empirical grounds for studies in the next two chapters of this dissertation.

This study also suggests a few areas for future work. Above all, in this chapter I demonstrate how one can include analyst recommendations as a dependent variable in linear models to examine the influence of financial measures on analysts' rankings. Via ordered probits, an analytical tool for discrete left-hand-side variables, future research may use recommendations to contemplate how specific signals convey information to the market or reflect factors affecting stock prices.[21] This proposal may particularly interest researchers who focus on studying financial signals for small firms or on exploring differential effects of financial signals on investors with heterogeneous levels of sophistication.[22]

Moreover, as an extension to this study, I will conduct inter-industry comparisons for influence of earnings forecast measures, market-model beta, and prior-period abnormal returns on analyst recommendations. The relation between market returns and accounting earnings as well as other financial measures may differ across industries. For example, firms with major goods or service lines that have extensive product life and firms with advantageous homogeneity or synergy in developing new products may have greater earnings persistence. Also, firms with products that require longer production/construction time are likely to be with low co-variance between changes in earnings and changes in firm values.[23]

Finally, researchers could explore other potential factors. This study demonstrates the ways in which estimates of accounting earnings help to explain analysts' firm-value

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21 Appendix 2 contains a more detailed discussion of potential research exploiting investment recommendations.

22 Still, Chapter 2 shows that analyst recommendations appear to be optimistic. Thus, future studies should identify specific subsets of analyst recommendations that could better serve as an analytical tool.

23 Several analysts who follow companies with relatively large transitory earnings components have explicitly stated that accounting earnings sometimes do not serve as an important variable to their recommendation ratings. For instance, in his December 5, 1988, research report on Rowan Companies, Everett G. Titus, III of Tucker Anthony wrote, "... *Within the offshore drilling group, perceptions are far more important than actual earnings results...*" (Wall Street Transcript, Page 92,183, 89/01/09)

expectation changes. However, the objective of this study is not to exhaust potential factors that influence analysts' rankings. There remain other factors that may interest accountants. For example, one could start by adopting earnings surprise an as explanatory variable.[24]

[24] In this proposed study, one can define an earnings surprise measure, UE as (AEPS - Fy1)/ price, where AEPS denotes Actual EPS, and Fy1 denotes the most recent analyst current-year EPS forecast.

Appendix 1

Survey On Major Security Analysts' *Buy/Hold/Sell* Ratings

1. For how many companies do you regularly provide earnings forecasts or buy/hold/sell recommendations? ________. What industries are these companies in? (Please name the two industries with the most companies you follow)____
__________.

Count	Sample Size	Mean # of Companies
42	40	21.2875

2. When you make a "Buy" recommendation on a specific company's stocks, what investment horizon do you typically think of?

__ (i). The stock price would rise within <u>one week</u>.
__ (ii). The stock price would rise within <u>two weeks</u>.
__ (iii). The stock price would rise within <u>one month</u>.
__ (iv). The stock price would rise within <u>two months</u>.
__ (v). The stock price would rise within <u>six months</u>.
__ (vi). None of the above. In fact, it's ______________
____

Choice	N	Percentage (%)
(i). Within 1 Week	0	0.00 %
(ii). Within 2 Weeks	0	0.00 %
(iii). Within 1 Month	0	0.00 %
(iv). Within 2 Months	2	5.00 %
(v). Within 6 Months	12	30.00 %
(vi). Within 6-12 Months	7	17.50 %
Within 1 Year	9	22.50 %
Within 12-18 Months	5	12.50 %
Within 1- 2 Years	2	5.00 %
Others	3	7.50 %
Total	40	100.00 %

3. Please choose one of the follows:

__ (i). I typically issue a recommendation for a single holding period for a company's stock.

__ (ii). Besides recommendations for the short term, I sometimes include long term ratings in my report.

__ (iii). Sometimes long term recommendation ratings are also included in my report, especially when my short term opinion is "Sell" or "Hold".

__ (iv). I always issue reports with both short term and long term opinions.

__ (v). None of the above. In fact, I ____________________ .

Choice	N	Percentage (%)
(i). Typically Issues It for a Single Holding Period	21	52.50 %
(ii). Sometimes Also Has Long Term Ratings	2	5.00 %
(iii). Sometimes Also Has Long Term Ratings, Especially When Short Term Opinion Is "Sell" or "Hold"	3	7.50 %
(iv). Always Issues Both Short Term and Long Term Opinions	7	17.50 %
(v). Others	7	17.50 %
Total	40	100.00 %

If your answer is (ii), (iii), (iv) or (v), please specify the lengths of holding periods you think of:

By <u>short term</u>, I mean
__ 1 week __ 2 weeks __ 1 month __ 2 months __ 6 months
__ None of the above, it's ______________________.

Choice	N	Percentage (%)
(i). 1 Week		%
(ii). 2 Weeks		%
(iii). 1 Month	1	5.56 %
(iv). 2 Months	5	27.78 %
(v). 6 Months	9	50.00 %
(vi). 1 Year	2	11.11 %
> 1 Year	1	5.56 %
Total	18	100.00 %

By <u>long term</u>, I mean
__ 3 to 6 months __ 6 to 12 months
__ 12 to 24 months __ 24 to 36 months
__ None of the above. It's ______________________.

Choice	N	Percentage (%)
(i). 3 - 6 Months	1	3.57 %
(ii). 6 - 12 Months	9	32.14 %
(iii). 12 - 24 Months	10	35.71 %
(iv). 24 - 36 Months	3	10.71 %
(v). 6 - 18 Months	1	3.57 %
12 - 36 Months	2	7.14 %
> 1 Year	1	3.57 %
5 Year	1	3.57 %
Total	28	100.00 %

4. On average, how often do you review a company's rating?

__ (i). Once a week
__ (ii). Twice a month
__ (iii). Once in every month
__ (iv). Once every two months
__ (v). Once every three months
__ (vi). None of the above. It's on average ______________.

Choice	N	Percentage (%)
(i). Once a Week	7	17.50 %
(ii). Twice a Month	1	2.50 %
(iii). Once a Month	7	17.50 %
(iv). Once Every 2 Months	0	0.00 %
(v). Once Every 3 Months	5	12.50 %
(v). Constantly	11	27.50 %
Daily	2	5.00 %
Depends/No Rule	4	10.00 %
Others	3	7.50 %
Total	40	100.00 %

5. On average, how often do you change a company's rating?

__ (i). Once a week
__ (ii). Twice a month
__ (iii). Once in every month
__ (iv). Once every two months
__ (v). Once every three months
__ (vi). None of the above. It's on average ______________.

Choice	N	Percentage (%)
(i). Once a Week	0	0.00 %
(ii). Twice a Month	0	0.00 %
(iii). Once in every Month	1	2.50 %
(iv). Once every 2 Months	0	0.00 %
(v). Once every 3 Months	8	20.00 %
(vi). Once in Every 6 M	2	5.00 %
Once in Every 6- 9 M	4	10.00 %
Once in Every 6-12 M	3	7.50 %
Once in Every Year	4	10.00 %
Depends	8	20.00 %
Others	10	25.00 %
Total	40	100.00 %

6. Please indicate how important the following variables are for forming or changing your recommendations on a company's stocks by choosing scale 1 - 5 for each of them:

1 = Not Important
2 = Somewhat Important
3 = Moderately Important
4 = Very Important
5 = Extremely Important

__ Risk Level of the Firm
__ Its Current Share Price
__ The Previous Changes in Share Price
__ Current Dividend Pay-out Ratio
__ Expected Cash Dividend Growth Rate
__ Expected Stock Dividend Growth Rate
__ Expected Earnings Growth Rate
__ One-Year-Ahead Earnings Estimate
__ Two-Year-Ahead Earnings Estimate
__ Predictability in Its Future Earnings
__ Predictability in Its Future Price-Earnings Ratios
__ Merger/Acquisition or Leverage-Buy-Out Potential
__ The Percentage of Institutional Investors' Share-holdings
__ The Number of Analysts Who Are Following the Company
__ Other Important Variables such as ____________________

____.

Variables	Mean	Std. Dev.	N
Risk Level of the Firm	3.56	0.93	36
Its Current Share Price	4.62	0.87	39
The Previous Changes in Share Price	2.42	1.12	38
Current Dividend Pay-out Ratio	2.00	1.10	38
Expected Cash Dividend Growth Rate	2.13	1.24	38
Expected Stock Dividend Growth Rate	1.54	0.95	37
Expected Earnings Growth Rate	4.41	0.87	39
One-Year-Ahead Earnings Estimate	4.33	0.80	39
Two-Year-Ahead Earnings Estimate	4.00	1.02	40
Predictability in Its Future Earnings	3.87	0.94	39
Predictability in Future P-E Ratios	3.04	1.04	36
Merger/Acquisition or LBO Potential	2.44	1.10	39
The Percentage of Institutional Investors' Share-holdings	1.84	0.67	38
# Analysts Following the Company	1.89	0.85	38
Other Important Variables such as			

7. Among all the reports in which you offer your opinions,

for what percentage of them do you maintain the ratings?
__________%

for what percentage of them do you up-grade the ratings?
__________%

for what percentage of them do you lower the ratings?
__________%

Change of Ratings	N	Percentage (%)
% Up-Graded > % Down-Graded	5	12 %
% Up-Graded < % Down-Graded	1	2 %
% Up-Graded = % Down-Graded	21	49 %
NA	16	37 %
Total	43	100 %

8. On average, how often do you make revisions on your one-year-ahead earnings forecasts of a company?

__ (i). Once a week
__ (ii). Twice a month
__ (iii). Once in every month
__ (iv). Once every two months
__ (v). Once every three months
__ (vi). None of the above. It's on average ______________

____.

Choice	N	Percentage (%)
(i). Once a Week	0	0.00 %
(ii). Twice a Month	0	0.00 %
(iii). Once in Every Month	5	12.50 %
(iv). Once Every 2 Months	10	25.00 %
(v). Once Every 3 Months	18	45.00 %
(vi). None of the Above	7	17.50 %
		%
Total	40	100.00 %

9. On average, how often do you make revisions on your two-year-ahead earnings forecasts of a company?

__ (i). Once a week
__ (ii). Twice a month
__ (iii). Once in every month
__ (iv). Once every two months
__ (v). Once every three months
__ (vi). None of the above. It's on average ____________

____.

Choice	N	Percentage (%)
(i). Once a Week	0	0.00 %
(ii). Twice a Month	0	0.00 %
(iii). Once in Every Month	1	2.63 %
(iv). Once Every 2 Months	5	13.16 %
(v). Once Every 3 Months	19	50.00 %
(vi). None of the Above	13	34.21 %
Total	38	100.00 %

10. You usually issue a "Buy" recommendation when you expect a company's stock would

__ (i). have an **upward price movement** in the near future

__ (ii). have a **greater than average return** in the near future (relative to all other stocks or other stocks in the same industry)

__ (iii). have **large positive risk-adjusted returns** in the near future

__ (iv). have **large positive risk- and typical individual investors'-transaction-cost-adjusted returns**

__ (v). None of the above. It's usually ______________

____.

Choice	N	Percentage (%)
(i). Price Moving Up in the Near Future	11	27.50 %
(ii). Greater Than Average Return	15	37.50 %
(iii). Large Positive Risk-Adjusted Returns	7	17.50 %
(iv). Large Positive Risk-&Typical Investors'-Transaction-Cost-Adjusted Returns	1	2.50 %
(v). None of the Above	6	15.00 %
Total	40	100.00 %

Please specify your preference by checking one or more of the follows:

__ Please send me a copy of the executive summary of the research paper on analysts' recommendations.

__ Please send me a copy of the research paper on analysts' recommendations

__ Please feel free to disclose that I participated in this survey.

....

Thanks very much for your time. Please feel free to mail this to us in the enclosed envelope.

Appendix 2

Analyst recommendation measures can serve as complements to abnormal security returns in empirical accounting research. In general, recommendations can be used as a dependent variable to help check the specifications of market reaction tests. In particular, for studies focusing on small firms or studies exploring differential effects of specific signals on financial information users with differential levels of sophistication, analyst recommendation rankings may outperform abnormal returns in exploring how accounting signals convey information to the market or reflect factors affecting stock prices.[25]

With the assumption that EMH is descriptive, Ball and Brown (1968) and Beaver (1968) began an extensive financial accounting literature that examines mean abnormal returns, variance of abnormal returns, and higher moments of abnormal return distributions in order to investigate the relative *importance* and *timeliness* of information in accounting signals. However, especially for studies of firms with low market liquidity, abnormal return tests are often liable to bias in selecting event windows.[26] Moreover, these tests are ineffective in exploring whether or how sophisticated financial statement users would react differently from other market participants to, say, footnote disclosure or legal disputes. For further information, researchers often perform time-consuming tasks of reading qualitative opinions in analysts' research reports.

In contrast, analyst recommendations have strong potential to help detect the information content in accounting signals. First, empirical studies using recommendations as a dependent variable require weaker assumptions of how the market price would converge to the conditional net present value given specific signal outcomes.[27] Second,

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25 Another potential indicator for financial statement users' revising their beliefs of firm values is changes in institutional investors' holdings. However, these seemingly sophisticated market participants are found by Lang and McNichols (1992) to be subject to incentives to "window dress." Institutional investors appear to selectively shift their portfolios at period end to change potential investors' perceptions of the return or the riskiness on the portfolio. Also, institutions only disclose holdings at quarter-ends. And thus data of changes in holdings may be insufficient for in-depth studies. Furthermore, their portfolios may be constructed with different tax considerations since institutions have different tax brackets.

26 However, note that there exists a limitation that analyst recommendation measures can supplement abnormal security return measures. Low market liquidity firms are also the least likely ones analysts would follow.

27 In general, these studies only require that, other things being equal, security prices would converge in the foreseeable future - so that the sophisticated market participants would trade on the new signals.

whereas both analyst recommendations and abnormal return measures can reflect how sophisticated users of financial information change their firm value expectations, tests using recommendations as an analytical tool are not exposed to the complexities of differential transaction properties regarding *market liquidity* of the securities.[28] Third, by including these tests in the studies, capital market price research can gain insights as to whether investors are heterogeneous in responding to specific accounting signals.

No prior empirical accounting or finance studies have explored such potentials. Above all, on-line database for analyst recommendations was not available until recently. Furthermore, analyst recommendations are discrete data, for which the conventional OLS model may not be appropriate because it assumes that the dependent variable is continuous.[29]

To deal with the latter problem, as shown in this study, one can use ordered probit models. This specification is a statistical tool for analyzing discrete dependent variables and can also be used to test how accounting or finance measures of interest affect analysts' recommendation ratings.

28 The differences among equity securities in transactional properties are likely to inconvenience researchers' selection of event windows and thus account for under- or over-estimates of potential information content in accounting signals. Wide-event-window designs inevitably insinuate noises. On the other hand, short event windows may be biased against capturing the full reactions of the market. Unfortunately, it is difficult for researchers to estimate how quickly investors would react to specific events for individual securities or even for overall samples.

29 Cross-sectional regression also requires that at any point of time all firms have the same coefficient for various relationships. The power of the regression test would be questionable when the assumption is violated.

Table 1
Sample Information

Panel A: Coverage Information of Analysts' Investment Recommendations, Earnings Forecasts, and EPS Growth Rate Estimates for Standard and Poor's 500 Firms

	Number
Analyst-Company Combinations with *Fy1* Forecasts Available in Research Holdings Limited Database:	16,535
Among these Observations,	
- Analyst-Company Combinations with *Fy2* Forecasts:	3,896
- Analyst-Company Combinations with *Fy3* Forecasts:	4
- Analyst-Company Combinations with *GROWTH* Estimates:	4,812
- Analyst-Company Combinations with *REC* Ratings:	15,449
- Analyst-Company Combinations with *REC* Ratings Available:	15,469
- Analyst-Company Combinations Where *REC* Ratings Are Available But EPS Estimates Are Not Available:	20

Panel B: Coverage Information of Analysts' Recommendations, Earnings Forecasts, and EPS Growth Rate Estimates for 540 Non-S & P Firms

	Number
Analyst-Company Combinations with *Fy1* Forecasts Available in Research Holdings Limited Database:	4,254
Among these Observations,	
- Analyst-Company Combinations with *Fy2* Forecasts:	1,615
- Analyst-Company Combinations with *Fy3* Forecasts:	10
- Analyst-Company Combinations with *GROWTH* Estimates:	808
- Analyst-Company Combinations with *REC* Ratings:	3,446
- Analyst-Company Combinations with *REC* Ratings Available:	3,613
- Analyst-Company Combinations Where *REC* Ratings Are Available But EPS Estimates Are Not Available:	130

Fy1: Current-Year EPS Estimate
Fy2: Subsequent-Year EPS Estimate
Fy3: Three-Year-Ahead EPS Estimate
GROWTH: Five-Year EPS Growth Estimates
REC: Analyst Investment Recommendations

Table 2
Ordered Probit Analysis - Analyst Earnings Estimates As a Factor to Analyst Investment Recommendations

Column	S&P 500	t	Non-S&P	t
Panel A: Model $REC = \beta o + \beta_{FY1REV}\, FY1REV + \varepsilon$				
N	12,855		2,392	
βo	0.69	(56.4)	0.52	(19.2)
β_{FY1REV}	-2.47	(-14.4)	-2.50	(-4.5)
Ln(L)	-16,924		-3,059	
Exp(Ln(L)/N)	0.268		0.278	
Panel B: Model $REC = \beta o + \beta_{FY2REV}\, FY2REV + \varepsilon$				
N	1,198		421	
βo	0.49	(12.9)	0.46	(7.3)
β_{FY2REV}	-4.93	(-6.1)	-9.29	(-5.3)
Ln(L)	-1,593		-512	
Exp(Ln(L)/N)	0.265		0.296	
Panel C: Model $REC = \beta o + \beta_{GROWTH}\, GROWTH + \varepsilon$				
N	1,774		399	
βo	1.13	(22.3)	1.37	(8.7)
β_{GROWTH}	-2.54	(-8.7)	-3.79	(-4.6)
Ln(L)	-2,221		-501	
Exp(Ln(L)/N)	0.286		0.285	
Panel D: Model $REC = \beta o + \beta_{FY1REV}\, FY1REV + \beta_{FY2REV}\, FY2REV + \varepsilon$				
N	646		259	
βo	0.43	(8.4)	0.40	(4.9)
β_{FY1REV}	0.19	(0.1)	-7.31	(-2.0)
β_{FY2REV}	-3.19	(-1.7)	-13.23	(-5.1)
Ln(L)	-839		-290	
Exp(Ln(L)/N)	0.273		0.326	

This table presents maximum likelihood estimates of the ordered probit models of analyst recommendations versus analyst EPS forecast revisions or EPS growth estimates. Standard errors in these analyses are computed from covariance of analytic first derivatives (Berndt, Hall, Hall and Hausman, or BHHH algorithm). The results are also robust to specification checks deriving standard errors either from analytic second derivatives (Newton) or from analytic first and second derivatives (Eicker-White). Test group *S&P 500* (*Non-S&P*) consists of all analyst recommendations for Standard and Poor's 500 firms (540 randomly selected Non-S&P firms). *REC* denotes the level of recommendation. *FY1REV* (*FY2REV*) denotes the contemporaneously released current-year (subsequent-year) EPS forecast revision for the same company-analyst combination deflated by close price at trading day -61, where day 0 is the recommendation date. *GROWTH* denotes the contemporaneously released five-year EPS growth estimate for the same company-analyst combination. Ln(L) denotes log of likelihood function. Exp(Ln(L)/N) serves as a measure of hit rate. The test period for Panels A, B, and D (Panel C) is from July 1987 (July 1991) to August 1992.

Table 3
Pre-Recommendation Market-Model Beta As a Factor to Analyst Investment Recommendations - Results of Ordered Probit Analysis for Model $REC = \beta o + \beta_{BETA}\, BETA + \varepsilon$

Panel A: Standard and Poor's 500 Firms (t-statistics in the parenthesis)

Column	1987	1988	1989	1990	1991	1992
N	1,135	14,959	12,606	11,038	11,399	4,354
βo	1.00	0.75	0.86	0.84	0.86	0.84
$t(\beta o)$	(8.8)	(23.1)	(25.8)	(25.6)	(29.8)	(18.3)
β_{BETA}	-0.30	-0.18	-0.05	-0.13	-0.10	-0.17
$t(\beta_{BETA})$	(-2.9)	(-6.5)	(-1.9)	(-4.8)	(-4.4)	(-4.7)
Ln(L)	-1518	-19950	-17804	-15310	-15776	-6052
Exp(Ln(L)/N)	0.263	0.264	0.244	0.250	0.251	0.249

Panel B: 540 Randomly Selected Non-S&P Firms (t-statistics in the parenthesis)

N	βo	$t(\beta o)$	β_{BETA}	$t(\beta_{BETA})$	Ln(L)	Exp(Ln(L)/N)
8,083	0.66	(23.7)	-0.04	(-1.6)	-10823	0.262

This table presents maximum likelihood estimates of the ordered probit models of analyst recommendations versus pre-recommendation BETA of the company. Standard errors in these analyses are computed using BHHH algorithm. The results are also robust to specification checks deriving standard errors either from analytic second derivatives (Newton) or from analytic first and second derivatives (Eicker-White).

REC denotes the level of analyst recommendation. *BETA* denotes the slope coefficient estimate of the market model with pre-recommendation estimation period [-292, -42]. Ln(L) denotes log of likelihood function. Exp(Ln(L)/N) serves as a measure of hit rate. In Panel B, to the immediate right of each parameter estimate is the corresponding t-statistic. The test period for both panels is from July 1987 to August 1992.

Table 4
Ordered Probit Analysis - Pre-Recommendation Abnormal Returns As a Factor to Analyst Investment Recommendations

Panel A: Standard and Poor's 500 Firms (t-statistics in the parenthesis)

Column	1987	1988	1989	1990	1991	1992
Model REC $= \beta o + \beta_{CARN60}$ ***CARN60*** $+ \varepsilon$						
N	1,153	15,087	12,783	11,117	11,494	9,770
βo	0.71	0.55	0.80	0.71	0.72	0.71
$t(\beta o)$	(17.3)	(50.0)	(63.9)	(54.3)	(54.1)	(50.6)
β_{CARN60}	-0.79	-0.11	-0.50	-0.85	-0.49	-0.47
$t(\beta_{CARN60})$	(-3.3)	(-1.6)	(-6.6)	(-13.2)	(-7.4)	(-6.4)
Ln(L)	-1541	-20135	-18018	-15350	-15890	-13233
Exp(Ln(L)/N)	0.263	0.263	0.244	0.251	0.251	0.258
Model REC $= \beta o + \beta_{CARN10}$ ***CARN10*** $+ \varepsilon$						
N	1,153	15,087	12,783	11,117	11,494	9,770
βo	0.69	0.55	0.80	0.70	0.74	0.72
$t(\beta o)$	(17.1)	(50.4)	(63.9)	(53.7)	(56.7)	(51.5)
β_{CARN10}	-1.07	-0.17	-0.62	-1.40	-0.80	-1.03
$t(\beta_{CARN10})$	(-2.2)	(-1.0)	(-3.6)	(-9.6)	(-5.9)	(-6.0)
Ln(L)	-1545	-20136	-18031	-15388	-15900	-13236
Exp(Ln(L)/N)	0.262	0.263	0.244	0.251	0.251	0.258

Panel B: 540 Randomly Selected Non-S&P Firms (t-statistics in the parenthesis)

Column	$\beta_1 = \beta_{CARN60}$	t	$\beta_1 = \beta_{CARN10}$	t
N	9,947		9,947	
βo	0.59	(43.8)	0.60	(44.5)
β_{CARN60}	-0.75	(-13.6)		
β_{CARN10}			-1.00	(-8.3)
Ln(L)	-13141		-13196	
Exp(Ln(L)/N)	0.267		0.265	

This table presents maximum likelihood estimates of the ordered probit models of analyst recommendations versus pre-recommendation cumulative beta-adjusted returns of the company. Standard errors in these analyses are computed using BHHH algorithm. The results are also robust to specification checks deriving standard errors either from analytic second derivatives (Newton) or from analytic first and second derivatives (Eicker-White). *REC* denotes the level of analyst recommendation. *CARN60* (*CARN10*) denotes the cumulative abnormal returns during the period [-60, -1] ([-10, -1]). Ln(L) denotes log of likelihood function. Exp(Ln(L)/N) serves as a measure of hit rate. The test period for both panels is from July 1987 to August 1992.

Table 5
Results of Multiple-Factor Ordered Probit Analyses

Panel A: FY1REV As the Measure of Unexpected Earnings

Column	S&P 500	t	Non-S&P	t
Model $REC = \beta o + \beta_{FY1REV}\, FY1REV + \beta_{BETA}\, BETA + \beta_{CARN60}\, CARN60 + \varepsilon$				
N	646		259	
βo	1.13	(8.93)	0.28	(1.49)
β_{FY1REV}	-1.30	(-0.66)	-5.49	(-2.44)
β_{BETA}	-0.52	(-6.16)	0.07	(0.51)
β_{CARN60}	-0.83	(-2.87)	-0.87	(-2.89)
Ln(L)	-818		-295	
Exp(Ln(L)/N)	0.282		0.320	
Model $REC = \beta o + \beta_{FY1REV}\, FY1REV + \beta_{BETA}\, BETA + \beta_{CARN10}\, CARN10 + \varepsilon$				
N	646		259	
βo	1.19	(9.55)	0.28	(1.46)
β_{FY1REV}	-1.48	(-0.69)	-5.82	(-2.47)
β_{BETA}	-0.55	(-6.56)	0.08	(0.54)
β_{CARN10}	-1.42	(-2.15)	-1.84	(-2.23)
Ln(L)	-819		-295	
Exp(Ln(L)/N)	0.281		0.320	

Panel B: FY2REV As the Measure of Unexpected Earnings

Column	S&P 500	t	Non-S&P	t
Model $REC = \beta o + \beta_{FY2REV}\, FY2REV + \beta_{BETA}\, BETA + \beta_{CARN60}\, CARN60 + \varepsilon$				
N	646		259	
βo	1.13	(8.91)	0.35	(1.87)
β_{FY2REV}	-2.18	(-1.21)	-11.96	(-4.35)
β_{BETA}	-0.52	(-6.14)	0.03	(0.22)
β_{CARN60}	-0.81	(-2.77)	-0.83	(-2.55)
Ln(L)	-817		-288	
Exp(Ln(L)/N)	0.282		0.329	
Model $REC = \beta o + \beta_{FY2REV}\, FY2REV + \beta_{BETA}\, BETA + \beta_{CARN10}\, CARN10 + \varepsilon$				
N	646		259	
βo	1.18	(9.49)	0.35	(1.83)
β_{FY2REV}	-3.01	(-1.67)	-11.67	(-4.25)
β_{BETA}	-0.55	(-6.53)	0.04	(0.24)
β_{CARN10}	-1.46	(-2.19)	-1.54	(-1.82)
Ln(L)	-819		-289	
Exp(Ln(L)/N)	0.281		0.328	

Table 5(continued)

Panel C: With Both FY1REV and FY2REV Included in the Model:

Column	S&P 500	t	Non-S&P	t
Model $REC = \beta_o + \beta_{FY1REV}\, FY1REV + \beta_{FY2REV}\, FY2REV + \beta_{BETA}\, BETA + \beta_{CARN60}\, CARN60 + \varepsilon$				
N	646		259	
β_o	1.13	(8.90)	0.34	(1.80)
β_{FY1REV}	-0.58	(-0.30)	-6.36	(-1.77)
β_{FY2REV}	-1.98	(-1.00)	-12.45	(-4.66)
β_{BETA}	-0.52	(-6.14)	0.04	(0.31)
β_{CARN60}	-0.81	(-2.77)	-0.77	(-2.42)
Ln(L)	-817		-287	
Exp(Ln(L)/N)	0.282		0.330	
Model $REC = \beta_o + \beta_{FY1REV}\, FY1REV + \beta_{FY2REV}\, FY2REV + \beta_{BETA}\, BETA + \beta_{CARN10}\, CARN10 + \varepsilon$				
N	646		259	
β_o	1.18	(9.49)	0.34	(1.77)
β_{FY1REV}	-0.43	(-0.22)	-6.71	(-1.86)
β_{FY2REV}	-2.86	(-1.45)	-12.19	(-4.47)
β_{BETA}	-0.55	(-6.52)	0.05	(0.33)
β_{CARN10}	-1.46	(-2.19)	-1.41	(-1.64)
Ln(L)	-819		-288	
Exp(Ln(L)/N)	0.281		0.329	

This table presents maximum likelihood estimates of the ordered probit model, $REC = \beta_o + \beta_{FY1REV}\, FY1REV + \beta_{FY2REV}\, FY2REV + \beta_{BETA}\, BETA + \beta_{CARN10}\, CARN10$ ($\beta_{CARN60}\, CARN60$) $+ \varepsilon$. The asymptotic standard covariance matrix of the parameter estimates are computed as the negative inverse of the matrix of first derivatives of the log-likelihood function with respect to the parameters (BHHH algorithm). The results are also robust to specification checks deriving standard errors either from analytic second derivatives (Newton) or from analytic first and second derivatives (Eicker-White). *REC* denotes the level of analyst recommendations. *FY1REV* (*FY2REV*) denotes the revision of current-year (subsequent-year) EPS forecast deflated by close price at trading day -61, where day 0 is the recommendation date. *BETA* denotes the slope coefficient estimate of the market model with pre-recommendation estimation period [-292,-42]. *CARN60* (*CARN10*) denotes the cumulative abnormal returns during the period [-60,-1] ([-10, -1]. Exp(Ln(L)/N) serves as a measure of hit rate. To the immediate right of each parameter estimate is the corresponding t-statistic. Test group *S&P 500* (*Non-S&P*) consists of all analyst recommendations for Standard and Poor's 500 firms (540 randomly selected non-S&P firms) from July 1987 to August 1992 that have contemporaneous *FY1REV* and/or *FY2REV* available in the Research Holdings Limited Database.

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Chapter 2: Security Market Reactions to Analysts' Recommendations

Abstract

By examining security price and trading volume changes accompanying and subsequent to analyst recommendations, I explore four questions related to the information in security analysts' earnings per share (EPS) forecasts and recommendations: (1) how do investors interpret analysts' recommendations, (2) do analysts' recommendations, earnings forecast revisions, and recommendation changes serve as sufficient statistics to one another, (3) does the market over-react or under-react to analysts' recommendations, and (4) does the type of organization that employs an analyst affect his recommendation behavior and investor response to his recommendations? These questions are fundamental to the role of analysts in a comprehensive system within which company-specific information is produced and used.

This study contributes to the contemporary accounting literature by providing a systematic and broad-based investigation of information content and sufficiency in analysts' recommendations and earnings forecasts. This is the first study to examine contemporaneous abnormal returns and volume to learn how investors perceive analyst recommendations. This study provides an innovative design for exploring the incremental information content of analysts' EPS forecasts and investment recommendations. Moreover, its evidence on whether and when investors over- or under-react to analyst recommendations helps enrich the contemporary literature of market irregularities.

1. Introduction

This study examines security price and trading volume changes accompanying and subsequent to analyst recommendations for Standard & Poor's 500 companies (hereafter *S & P 500 firms*) and for 540 randomly selected non-Standard and Poor's 500 companies (hereafter *Non-S & P firms*).[1] Specifically, it explores four questions related to the information content of security analysts' earnings per share (EPS) forecasts and recommendations. First, this study explores how investors interpret analysts' recommendations, examining both perceived objectiveness and perceived informativeness of these signals. The informativeness of these signals defines the role of security analysts as information intermediaries. As Jack Rivkin, director of equity research at Shearson Lehman Hutton stated,

> An analyst's role is to develop and provide an informed, objective opinion regarding the future of a company or an industry and make some determination about the value of the securities of those entities. The analyst is an arbiter of values between the issuers and the investors. He is required to gather and sift through all types of information from sources each with their own biases. (Rivkin, 1990)

My investigation of whether analysts act as objective arbiters of firm value information focuses on detecting whether their ranking behavior is strategic, and, if so, the implication for security prices. Bias in research or brokerage firms' prospective reports may arise from analysts' reliance on lines of communication with corporate executives and/or pressure to curry favor with client companies. Investment recommendations, as the most direct signal for security analysts' anticipated changes in firm values, should reflect analysts' strategic behavior and investors' adjusting for research report bias most evidently. In addition to the potential for recommendation bias, coarseness and vagueness are also characteristics of analysts' opinion reports. By examining contemporaneous abnormal price and volume changes, this study also explores whether these potential limitations make analyst recommendations uninformative.

Second, I investigate whether contemporaneously released analyst recommendations and analyst earnings forecast revisions serve as sufficient statistics for each other. On the one hand, accounting earnings, as well as analysts' current- and subsequent-year EPS forecasts, may be viewed as measuring underlying economic earnings with error, especially for companies with substantial transitory components. On

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1 The sample of *S & P 500 firms* consists of the five hundred companies listed in the June, 28, 1991, issue of *Stocks in the Standard & Poor's 500* published by Standard & Poor's Corporation.

the other hand, investment recommendations may not fully reflect security analysts' firm value expectations as a result of analysts' strategic ranking behavior, analysts' vagueness in specifying investment horizons, investors' heterogeneous levels of tolerance toward risk, and investors' non-trivial differences in transaction costs. Because investment recommendations and earnings forecasts each may be limited in their ability to fully reveal an analyst's price performance expectation, investors may find both earnings forecasts and recommendations informative. Examining incremental information content of analysts' earnings forecasts and analysts' recommendations, this study aims to investigate investors' financial information inputs.

Third, this study examines post-recommendation abnormal returns and explores potential factors that may explain their variability. It investigates whether investors fail to fully adjust for bias and/or fail to appropriately exploit the implications of recommendations. Furthermore, it seeks empirical evidence on whether investors' perception of the informativeness of analysts' *buy/hold/sell* opinions and the extent of competing signals account for over- or under-reactions to recommendations. Specifically, this study provides evidence concerning seven potential factors that influence the magnitude of post-recommendation price drifts or price reversals: richness of the company's routine information flows, perceived information content of the signals, extent of counteracting information, the type of agency the analyst belongs to, the strength of the analyst's firm's sales force, levels of publicity, and market liquidity of securities.[2]

Fourth, it investigates whether the type of organization that employs an analyst affects his ranking behavior and investors' response to his recommendations. Specifically, I explore whether brokerage-firm analysts, who may encounter pressure from the firms' revenue generating divisions, are more reluctant to issue unfavorable recommendations than non-brokerage analysts. I also test whether brokerage analysts, who may have stronger incentives and better opportunity to gather non-public information, make more informative recommendations than non-brokerage analysts.

These questions interest accounting researchers for several reasons. First, this study contributes to our understanding of strategic behavior by security analysts. As Schipper (1991) notes,

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[2] Kyle (1985) states that the transactional properties regarding market liquidity include *tightness* (the cost of turning around a position over a short period of time), *depth* (the size of an order flow innovation required to change prices a given amount), and *resiliency* (the speed with which prices recover from a random, uninformative shock). In a liquid market, prices would eventually converge to their underlying value.

> The focus of accounting research on analysts' forecasts is essentially a focus on just one part of the total responsibilities of a financial analyst; the question arises, how would we view these forecasts and their properties if we studied them as an input to the ultimate analyst judgment -- what recommendation to make on a stock... Forecasting earnings is by definition subordinate to the goal of picking stocks and writing reports which support those judgments.

Investment recommendations, as the most direct signal for security analysts' anticipated changes in firm values, should reflect analysts' strategic behavior and investors' adjusting for research report bias most evidently. Second, it demonstrates investors' ability to detect and to adjust for strategic behavior. Third, it provides evidence concerning the informational role of earnings forecasts relative to recommendations. Fourth, investigations of security market behavior associated with analyst recommendations demonstrate the feasibility of adopting these measures to contemplate the *importance* and *timeliness* of information in accounting signals. As Chapter 1 proposes, analyst recommendations can complement abnormal returns in exploring how accounting signals convey information to the market or reflect factors affecting stock prices. This potential warrants a thorough examination of analyst recommendations, including their information content and bias. Fifth, by documenting post-recommendation announcement drifts as well as exploring whether investors' perceptions of their information providers and securities' transaction properties account for the systematic post-recommendation abnormal returns, this study adds to the contemporary literature of market irregularities.

This study contributes to the contemporary accounting literature by providing a systematic and broad-based investigation of information content and sufficiency in analyst recommendations. Most of the research on investment recommendations, such as the medium- and long-event-windowed abnormal return analyses by Copeland and Mayers (1982), Elton, Gruber, and Grossman (1986), and Womack (1993), focuses on analysts' stock-picking ability and test whether analysts' recommendations can be used to earn abnormal returns. This study is also related to an independent and contemporaneous study by Francis and Soffer (1993) that explores sufficiency in analyst recommendations and EPS forecasts for a sample of 100 firms with extremely positive or negative earnings surprises in 1989. They document that both recommendations and earnings forecast revisions have information content, and find stronger relative information content for earnings forecast revisions than does this study. However, it seems plausible that sampling on extreme earnings changes might bias their tests toward finding greater information content to earnings forecast revisions, because analyst forecasts in their sample are more likely to have significant price impacts. In contrast, this study includes all Standard &

Poor's 500 companies and 540 non-S&P companies to provide a descriptive picture for a comprehensive sample of firms and earnings realizations. Finally, on investigating announcement effects of investment recommendations, this study adopts a broader sample and examines a broader set of potential variables to post-recommendation returns than Barber and Loeffler (1993). Barber and Loeffler (1993) examine contemporaneous and post-announcement response to 95 *buy* recommendations for large companies that appeared in the monthly "Dartboard" column of the Wall Street Journal, whereas this study examines contemporaneous and post-announcement reactions for all five levels of recommendations and includes in its sample recommendations with various levels of publicity.

The next section contains a more detailed discussion of my tests for information content and bias in recommendations. Section 3 describes the data and the market model specifications. Section 4 provides evidence on how the investing public perceives analyst recommendations. Section 5 explores whether analyst earnings forecast revisions, analyst recommendations, and recommendation changes appear to serve as complementary or substitute sources of information to one another. Section 6 examines security price changes subsequent to the announcements of recommendations. Finally, Section 7 concludes the chapter and discusses areas for future work.

2. *Institutional Background and Hypotheses*

Security analysts, as information intermediaries, have been regarded as an important sector in the system that produces and uses company-specific information. As stated in Beaver (1989),

> The information network among executives and analysts may be the mechanism which permits security prices to promptly reflect a comprehensive information system.

This mechanism consists of two stages. First, analysts incorporate market, industry, and firm-specific information into their firm value expectation and base their investment recommendations, at least in part, on whether this suggests a firm's shares are under-valued or over-valued. Strategic factors may also motivate analysts to deviate from issuing unbiased recommendations. Second, investor response to analysts' research reports is reflected in stock price and volume changes. Focusing on market response to investment recommendations and earnings forecast revisions, this study provides evidence on the influence of these signals on investors' beliefs, and the extent to which investors adjust their beliefs for strategic behavior by analysts.

2.1 THE INFORMATION CONTENT OF ANALYST RECOMMENDATIONS

Analysts generally rank the equity securities in their universe with *strong buy*, *buy*, *hold*, *hold/sell*, or *strong sell* based on their price performance predictions.[3] Only a few analysts adopt finer ranking systems. Research reports are often vague about risk factors, anticipated price level, and the investment horizon.[4] This may reflect the difficulty of foreseeing upcoming events that could influence firm value, of calibrating for transactional properties that affect the market liquidity of securities, and of measuring investors' level of sophistication to promptly respond to these events.[5] However, despite the coarseness of these signals, the financial press regularly evaluates analysts' performance in making recommendations.[6] This anecdotal evidence is consistent with the notion that the investing public regards recommendations as a signal that may provide information about firm value.[7]

Moreover, it is likely that analysts working for different types of forecasting agencies may have differential levels of ranking performance. A necessary condition for a security analyst's recommendations to have information content is the analyst's ability to *systematically* outperform the average investor in predicting future firm values. For this superiority to persist, security analysts must either be more sophisticated processors of publicly available information than other investors, or more effective seekers of non-public

3 Some information intermediaries adopt numerical ranking systems. Also, some agencies use different terminology. Consistent with the categories adopted in Research Holdings Limited Database, the data source of recommendations for this study, this study adopts these representative rankings.

4 This phenomenon is inconsistent with most other ratings of prosperity or liquidity such as bond ratings (AAA to C). As information suppliers to investors, analysts may be able to gain efficiency in presenting their findings, as well as to differentiate themselves from less accurate forecasters by choosing finer measures with more scale levels or specified time horizons.

5 Other potential explanations for analysts' not choosing finer measures include: (1) It is not cost-effective to generate more than five levels of recommendations. The abnormal returns associated with finer measures are not large enough to justify the additional costs. (2) Analysts do not attempt to summarize their reports with the single variable of recommendation rating. Instead, they produce EPS forecasts and EPS growth estimates, together with other qualification remarks, to help demonstrate the risk profile, longer term prosperity, and changes in irregular items in earnings to investors with various investment horizons and risk tolerance levels.

6 The Wall Street Journal and Zacks Investment Research employ considerable resources in estimating how an investor would fare by buying every stock on the *recommended* list at fifteen major brokerage houses. See Dorfman (1993a), Dorfman (1993b) and Dorfman (1993c).

7 Chapter 1 finds analysts issue more favorable recommendations for securities with greater prior-period abnormal returns.

information. Consistently, Lees (1981) documents, interviews with company executives provide security analysts with their most important source of information.[8] However, whereas brokerage firm analysts have considerable opportunities to work closely with client companies on investment banking or corporate finance services, many non-brokerage analysts specialize *exclusively* on processing and interpreting public information.[9] Furthermore, brokerage firm analysts may have stronger incentives to collect non-public information. Consequently, brokerage analysts may have greater ability to predict these companies' prospects.

This study first examines both market reactions to overall samples and differences in market reactions among analysts of different types of forecasting agencies to explore the perceived information content in analyst recommendations.

H_{1a}: Contemporaneous security price and volume changes behave as if analyst recommendations are perceived to have information content.

H_{1b}: Contemporaneous security price and volume changes behave as if brokerage (non-brokerage) analyst recommendations are perceived to be more (less) informative.

There has been considerable concern in the market that analysts' *buy* (*hold*) rankings may be a euphemism for *hold* (*hold/sell*). Although reputational consideration and market discipline may help promote security analysts' objectivity, bias in prospective reports may arise from analysts' heavy reliance on their lines of communication with management for firm-specific information. As monopoly suppliers of private information, corporate executives who prefer favorable reports may either selectively provide favorable news or pressure analysts to bias up EPS forecasts and recommendations.[10] In addition, pressure from the firms' investment banking or corporate finance divisions may also jeopardize brokerage-firm analysts' objectivity.[11] Under conflicting pressure, despite the "Chinese Wall" rules that are intended to prevent corporate finance and other departments

8 Lees (1981) finds that analysts' sources of information, in order of importance, are (1) interviews with company executives, (2) 10-K's and other reports to the SEC, (3) shareholder reports, (4) management forecasts, and (5) formal presentations by company executives.

9 As an example, Copeland and Mayers (1982) reported that rankings provided by The Value Line are based on publicly available information.

10 If an executive is unhappy with an analyst's report, he may threaten to cut off the analyst's access to information about the firm. See Laderman, Hawkins, and Recio (1990).

11 Note that brokerage firm analysts provide a very large proportion of investment recommendations available to the investing public.

from exercising influence over analysts, systematic bias may still occur. First, over- or under-estimation of companies' earnings prospects may result from analysts' strategic withholding of favorable or unfavorable signals. Second, research report bias need not be intentional. For example, if an analyst is more likely to double-check his findings before issuing an unfavorable report than a favorable one, one would expect optimistic recommendations on average.[12]

As documented by Lin and McNichols (1993a), Lin and McNichols (1993b), Dugar and Nathan (1993), and Chapter 3 of this dissertation, analysts' incentives to maintain favorable relations with investment bank clients may influence their reports.[13] Lin and McNichols (1993a) find that investment bank analysts systematically recommend more favorably for their seasoned public offering clients. Lin and McNichols (1993b) provide evidence that analyst recommendations for IPO clients are more optimistic. Moreover, Dugar and Nathan (1993) document that investment banking relations correspond to over-estimates in analysts' forecasts and recommendations. Consistently, Chapter 3 presents evidence consistent with the notion that underwriter analysts bias up (down) their recommendations (EPS forecasts) for public utilities to curry favor with these companies' executives.[14]

In addition to underwriting business, other types of relationships in the investment banking and corporate finance fields can influence analysts' objectivity.[15] For fear of

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12 In the absence of perfect information regarding a company's prospects, a high possibility of valuation error may exist. The law of averages predicts that on average the predicted and the true values are approximately equal. Therefore, if there is a higher (lower) probability that a preliminary report that perceives the higher (lower) value in the company could get through the process, then the probability that the analysts' final report is overestimated is higher than the probability that it is underestimated.

Any empirical researchers who are more (less) inclined to reconstruct their analyses when the test results are inconsistent (consistent) with the prior are also subject to this type of bias.

13 Most prior studies related to analysts' strategic behavior focus on brokerage-firm analysts' earnings or return forecast bias. One exception is Francis and Philbrick (1992), who document that Value Line analysts' earnings forecasts are more optimistic for *sell* and *hold* stocks than *buy* stocks.

14 Lin (1993b) provides both anecdotal examples and statistical evidence supporting the hypothesis that public utilities manipulate their reported earnings for fear of regulatory rate interventions, re-regulation, or new entry. Also, Chapter 3 of this dissertation introduces a two-audience, two-signal model, suggesting that analyst recommendations (earnings forecasts) may exclusively affect investors' (regulators') decisions.

15 Among them, investing connections such as consulting businesses are difficult to identify. On the other hand, take-over activities may be easier to identify and could thus be a candidate for future research.

jeopardizing business relationships, brokerage firm analysts may be reluctant to make unfavorable recommendations for current or potential client companies.[16] Accordingly, brokerage analysts' *strong sell* or *hold/sell* recommendations may have stronger negative implications. These unfavorable measures may either reflect an excessively gloomy outlook or further signal the companies' low potential to become valuable business clients.

Investors may also respond differently to recommendations provided by different types of information intermediaries. First, unfavorable recommendations by brokerage (non-brokerage) analysts may be viewed as more (less) negative signals, given brokerage analysts' incentives to maintain business relationships. Second, because national analysts' recommendations receive substantial publicity and regular evaluation by the financial press, national (regional) analysts may provide less (more) optimistic recommendations. These analysts are more likely to value their reputation over their relationships with corporate executives than regional firm analysts, whose employers may view every communication channel as indispensable.

This study investigates recommendation bias via significance tests of security prices. Recognizing analysts' incentive to provide optimistic recommendations, investors may adjust for expected bias while revising their beliefs at the announcements of the rankings. Thus for my tests of the following hypotheses, contemporaneous abnormal returns reflect the extent to which analyst recommendations are perceived to be biased.

$\mathbf{H_{1c}}$: Contemporaneous security price changes behave as if investors perceive analyst recommendations to be upwardly biased.[17]

$\mathbf{H_{1d}}$: Contemporaneous security price changes behave as if brokerage (non-brokerage) analysts' unfavorable recommendations are perceived to be more (less) negative signals.

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16 A few recent articles in the financial press reported intensifying pressure on brokerage-firm analysts to help gain investment banking business or criticized brokerage firms' explicitly discouraging unfavorable recommendations. For example, Fisher (1984) wrote, "Some firms now push much greater emphasis on a role that the analysts always played to some extent - getting business for the investment banking side." Moreover, Dorfman (1991) reported, "At Raymond James & Associates, an analyst can gain 130 *production points* (which analysts are told to strive for) with a major *buy* recommendation. But a recommendation to *sell* or *hold* a stock is worth at most 60 points, no matter how carefully researched."

17 Prior research documents that analyst earnings forecasts are upward biased. However, since analysts seldom specify their implied investment horizon, researchers can not *objectively* measure analysts' recommendation performance by realized holding gains or losses. Moreover, long- and medium-windowed abnormal return tests do not provide sufficient evidence on how sophisticated investors appear to be, and therefore, what role analysts play as information intermediaries. Specifically, these tests do not reveal whether investors perceive analyst recommendations as being informative and whether investors undo recommendation bias.

H_{1e}: Contemporaneous security price changes behave as if national (regional) brokerage analysts' favorable recommendations are perceived to be more (less) informative signals.

2.2 THE *INCREMENTAL* INFORMATION CONTENT OF ANALYST RECOMMENDATIONS, CONTEMPORANEOUS FORECASTS OF EARNINGS, AND RECOMMENDATION CHANGES

Investment recommendations are not the only summary signal in analyst research reports. Most security analysts release both earnings forecasts and recommendations to convey their expectations to investors.[18] According to a survey I conducted in June 1992 (hereafter the *Survey*), only two analysts indicated they release recommendations without an earnings forecast.[19] This phenomenon may result from the fact that analysts' earnings forecasts have *incremental* information content about firm value. Analysts may release earnings estimates to allow investors with different levels of risk tolerance or different investment horizons to make appropriate decisions. However, there exist two other potential explanations. First, analysts may also include earnings forecasts as a signaling device to develop their credibility in forecast accuracy.[20] As compared with recommendations, analyst EPS forecasts are finer and more verifiable measures. Thus it may be easier for investors to compare analysts by their EPS forecast accuracy.[21] Second, analysts may merely *stick with a social norm* of disseminating their EPS forecasts as "work-in-progress" measures. As noted earlier, Schipper (1991) argues that the

18 This phenomenon is puzzling, since as information intermediaries, analysts could focus on only one signal to save information gathering and processing costs for themselves and for the investing public.

19 In this survey each of 130 randomly selected security analysts was sent a questionnaire. Forty-three of these analysts answered and returned the survey. However, only two out of the forty-three participants stated that they release EPS forecasts but not investment recommendations.

20 If analysts' EPS forecast accuracy serves as an effective signal, then analysts who make better EPS forecasts would tend to be the ones who issue more accurate ratings. In an extension to this study, I further explore these two research questions: (1) whether analysts' forecasting ability appears to be associated with their ranking performance, and (2) whether the market reactions to analyst recommendations appear to be stronger to issuers of more accurate earnings forecasts?

21 Because analysts provide their earnings estimates with specified earnings periods and magnitudes, investors may more easily rank the analysts by their EPS forecast accuracy. If this is the case, i.e., analysts' EPS forecast accuracy serves as an effective signal, then analysts who make better EPS forecasts would tend to be the ones who issue more accurate ratings. So the research question is (i) whether analyst' forecast ability appears to be associated with their ability to make "good" recommendations, and (ii) whether the market appears to respond more to the "credible" ones - are more accurate EPS forecasters viewed as issuers of more accurate recommendations?

analysts' earnings forecasting process may be one portion of a more complicated decision process designed to arrive at an investment recommendation.[22] Moreover, Chapter 1 of this dissertation documents that analysts' multiple-year earnings forecast revisions or five-year EPS growth estimates have significant explanatory power for the variation in their recommendations. It could be the case, as with industry and competition profiles and other major inputs to recommendations, that whereas analysts' recommendations are the main focus in the reports, their EPS forecasts are made public to support recommendation ratings.[23] Because of these possibilities, I adopt a capital market research methodology to explore whether analyst EPS forecasts (analyst recommendations) serve as a sufficient statistic about firm value for contemporaneous investment recommendations (EPS forecasts).

I examine contemporaneous security returns to test the following hypothesis:

H_{2a}: Security prices behave as if contemporaneous analyst earnings forecast revisions and analyst recommendations each provide incremental information to investors.

The level of recommendation, not the first difference, directly discloses an analyst's prediction regarding future returns of a security to investors. Regardless of whether an analyst assigns a ranking from 1 to 5 or assigns a ranking from *strong buy* to *strong sell* to the stocks, a better (worse) level indicates that more (less) favorable price performance is expected. However, most analysts' research reports disclose both the direction and magnitude of changes from their prior recommendations together with the levels of recommendations. This joint disclosure behavior may be a result of analysts' revealing their firm-value expectations through both levels and changes of recommendations. Alternatively, recommendation changes may help investors to evaluate corporate management's past performance or analysts' prior rating performance. Recognizing these possibilities, I also investigate whether recommendation changes are incrementally informative. Stated formally, I test:

H_{2b}: Security prices behave as if down-grading (up-grading) rating changes have negative (positive) information implications over and above the rating levels.

22 The notion that providing investment recommendations is analysts' most important task has the backing from some practitioners. For example, Gerald A. Rothstein, associate director of research at Oppenheimer & Co. says, "The fact that XYZ Co. makes a certain number of widgets a year in a plant is utterly useless unless it affects an opinion on a stock." (Fisher, 1984)

23 If this is the case, the research question would be: why the majority of analysts would choose to release work-in-progress? Could investor do better by incorporating the EPS forecast measures as well?

2.3 POST-ANNOUNCEMENT EFFECTS OF RECOMMENDATIONS AND THE INFLUENCE OF INFORMATION PROVIDED BY SOURCES OTHER THAN ANALYST RESEARCH REPORTS

Investor response to analyst recommendations upon their issuance may depend on the extent investors discount for expected bias in recommendations and counteracting signals as well as the richness of routine reports about the companies' prospects. First, encountering favorable recommendations, which are often unchallenged by other information providers, investors must correct for perhaps unanimous optimism. Second, corporate executives' attempts to deter unfavorable recommendations may keep investors from gaining insights from these signals. *Strong sell* or *hold/sell* recommendations, once released, can induce substantial counteractions such as supportive comments made by company executives and more optimistic analysts.[24] Third, routine reports or signals provided by sources other than security analysts can supplement investors' understanding of a company's prospects. For example, investors may be less inclined to over-react to analysts' favorable recommendations for large firms, which are more heavily covered by the financial press.

To investigate whether these factors are associated with investors' over- or under-reactions to recommendations, I test the following hypotheses:

H_{3a}: The magnitude of market under- or over-reactions to an analyst recommendation decreases with the richness of the company's routine information flows.

H_{3b}: The magnitude of investors' over-reactions to favorable recommendations increases with the perceived information content of the signals.

H_{3c}: The magnitude of investors' under-reactions to unfavorable recommendations increases with the extent of counteracting information.

3. *Data Description and Specifics*

3.1 ANALYSTS' FORECASTS AND RECOMMENDATIONS

One special feature of this study is its use of a large sample of analysts' earnings forecasts and recommendations (names of forecasting agencies and analysts, earnings estimates, recommendation ratings, and estimate/recommendation dates). The database, provided by Research Holdings Limited Inc., contains all EPS forecasts and recommendations made between July 1987 and July 1993 by sell-side analysts employed at two hundred and seventy-two dealer/broker firms or advisory service agencies. The list of forecast and

24 See Fisher (1984) and O'Glove (1987), which provide anecdotal examples that analyst *sell* recommendations invoke counteracting outcries from other analysts following the firms.

recommendation providers includes the major current information intermediaries as well as research agencies that have been merged or liquidated.[25] Table 1 provides descriptive evidence on frequency with which security analysts issue investment recommendations, current-year earnings forecasts (Fy1), and subsequent-year earnings forecasts (Fy2) during 1991-1992. This table shows that security analysts issue their Fy1 forecasts more frequently than their Fy2 forecasts and investment recommendations.

The sample includes two test groups, *S & P 500 firms* and 540 *Non-S & P firms* randomly selected from the set of all 1992 COMPUSTAT companies. Observations of *Non-S & P firms* serve as a hold-out test group for observations of *S & P 500 firms*. Also, I use the S & P 500 membership as a proxy for the corporate executive's power as a supplier of company-specific information, the richness of financial information from other sources, and the market liquidity of the security.[26]

3.2 TOTAL ASSETS, RETURNS, VOLUME, MARKET INDICES AND RISK-FREE RATES

This study uses other data items collected from the CRSP Database and the Citibase. Data items provided by CRSP include total asset measures, a proxy for firm size, on the Industrial COMPUSTAT tape as well as distribution factors and split dates for events such as stock split and stock dividends, closing prices, dividend-adjusted returns, trading volume, and market return indices on the Daily CRSP data tape. Data regarding one-year Treasury Bill yields are provided by the Citibase.

25 Selection bias could otherwise stem from exclusively examining existing agencies, of which the predictive superiority, by chance or by real strength, may contribute to their survival.

26 See Table 1 of Chapter 1, which presents analyst coverage information. For *S & P 500 firms*, 16535 (15469) analyst-company combinations are with current-year EPS forecasts (investment recommendations) available in the database. For *Non-S&P firms*, 4254 (3613) analyst-company combinations are with analysts' current-year EPS forecasts (recommendation ratings) available.

In this study, *S & P 500 Firms* (*Non-S&P Firms*) serve as representatives of large (small) companies listed at NYSE, AMEX, and NASDAQ. Larger firms are likely to have greater monopolistic power as suppliers of firm-specific information, richer financial information from sources other than security analysts, and greater level of market liquidity of their securities than do smaller firms.

3.3 SPECIFICS

This research defines the test period as the union of the 60-trading-day period prior to and the 150-trading-day period following analyst recommendations ([-60, -1] U [0, 150]).[27] The long-window tests adopt both [0, 60] and [0, 150] event period specifications to detect analysts' predictive ability for imminent events as well as longer-term events.[28] The short-window tests examining the market reactions to analyst recommendations adopt four specifications of event periods: [-2,0], [-2,1], [-2,2] and [-2,3], since it is difficult to isolate the price impact of the release of analyst research reports.[29]

The benchmark period for estimating market-model beta is defined as the union of [-500, -250] and [215, 339]. This study adopts the market model to control for market effects. In order to mitigate potential bias against detecting analyst's performance or post-announcement security price reversals, I exclude the calendar year prior to the recommendation date and the approximate three-calendar-month period immediately after the test period. This research design is in part motivated by Chapter 1, which documents that prior-period abnormal returns significantly influence analysts' recommendations.

4. Perceived Information Content and Bias in Investment Recommendations

4.1 DISTRIBUTION OF ANALYST RECOMMENDATION BY RANKING LEVEL AND TYPE OF INFORMATION INTERMEDIARY

Table 2 provides preliminary evidence that (1) analysts make disproportionately large (small) numbers of favorable (unfavorable) recommendations, and (2) analysts of different types of information intermediaries make differential percentages of favorable and unfavorable recommendations. Above all, as shown in Panels A and B, for national

27 Hereafter I define *[s, t]* as the period starting at the beginning of trading day *s* and ending at the end of trading day *t*, where day 0 is the recommendation date.

28 In this study, I adopt both long event windows of [0, 60] and [0, 150] to investigate analyst performance. Note that a security's cumulative abnormal returns would rise *immediately* after the release of analyst *strong buy* recommendation and then be flat only if (1) the analyst's predictive ability exists, (2) the market reacts appropriately to his recommendation, and, (3) the market is liquid enough. However, it is an empirical question as to whether all three conditions are met. Therefore, I use long event windows to mitigate bias against detecting analyst's performance and bias against detecting price reversals following investors' overreactions.

29 First, some analysts are likely to disseminate their findings to preferred clients or subscribers before the *research report date*, on which date the information intermediary issues the EPS forecasts and recommendations. Second, for each forecast or recommendation included in Research Holdings Limited Database, it is impossible to identify whether the report was issued before the market closed or whether the market was liquid enough to fully react to the announcement within a short period of time.

brokerage firm, regional brokerage firm, and non-brokerage analysts, favorable (*strong buy* and *buy*) recommendations all appear at least three times as frequent as unfavorable (*strong sell* and *hold/sell*) recommendations. For overall *S & P 500 firms* (*Non-S & P firms*), 47.8% (53.7%) of investment recommendations are *strong buy* or *buy*, whereas 11.5% (8.0%) of them are *strong sell* or *hold/sell*. Furthermore, this table demonstrates that the type of organization an analyst belongs to affects the percentage of favorable and unfavorable recommendations he provides. First, contingency test results shown in Panel C indicate that regional analysts issue a higher percentage of *strong buy* recommendations than do national analysts for both *S & P 500* and *Non-S & P* firms, suggesting they may be more concerned with currying favor with corporate executives. Second, consistent with the hypothesis that brokerage analysts are reluctant to issue unfavorable recommendations, Panel D demonstrates that, for both test groups, these analysts make a significantly smaller proportion of *strong sell* and *hold/sell* recommendations.

4.2 ABNORMAL RETURNS ACCOMPANYING ANALYST RECOMMENDATIONS

Sections 4.2 and 4.3 investigate market reactions to recommendations. Table 2 provides preliminary evidence that security analysts behave strategically. However, security analysts may strategically withhold recommendations that are unfavorable, or may issue biased research reports. For this reason, documentation of an asymmetric distribution of favorable and unfavorable recommendations is not conclusive as to whether *disclosed* recommendations are biased. Nor can it provide evidence as to whether the recommendations are perceived to be informative. Therefore, to further explore perceived information and bias in analyst recommendations, Sections 4.2 and 4.3 examine market price and volume changes accompanying the releases of these signals.[30]

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[30] Despite that security analysts may choose not to disclose their firm value anticipation, for the following reasons this potential of selection effect is not likely a significant issue in this study. Above all, this chapter focuses on exploring bias and informativeness of *disclosed* investment recommendations and earnings forecasts. Moreover, non-brokerage firms most typically provide their research reports periodically. For example, Value Line analysts do not have much leeway to exclude their recommendations from Value Line Investment Survey (Weekly Summary of Advises and Index.) Thus these observations are not likely to be subject to withholding problems. Furthermore, peer pressure, market discipline, and signaling incentives may help mitigate major security analysts' withholding their recommendations or forecasts for large companies such as *S & P 500* firms.

For purposes of making inferences of security analysts' predictive ability, however, one should use the empirical results of this study with caution, especially for brokerage firm analysts' price and earnings forecasts for *Non-S & P* firms. As it may be brokerage analysts' discretion to selectively withhold their favorable or unfavorable signals for small companies.

4.2.1 RESEARCH DESIGN

This section tests hypotheses $\mathbf{H_{1a}}$ to $\mathbf{H_{1d}}$, exploring whether analyst recommendations are perceived to have information content and/or bias by examining abnormal security returns accompanying their announcements. It groups securities into five portfolios, depending on the recommendation level (*strong buy, buy, hold, hold/sell,* or *strong sell*).

This study conducts significance tests of the beta-adjusted returns over event windows [-2,0], [-2,1], [-2,2] and [-2,3]. I estimate the market model for daily returns,

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt} \qquad (1)$$

for each observation, using CRSP Daily security return as R_{jt} and value-weighted daily market return as a proxy for R_{mt}.[31] Return prediction errors are compounded multiplicatively over the event interval. If contemporaneous abnormal returns differ across levels of recommendations, then the evidence is consistent with the hypothesis that analyst recommendations have information content. Moreover, if mean abnormal returns accompanying *hold* recommendations were to be significantly negative, it would be consistent with the hypothesis that the market regards *hold* as a euphemism for *sell.*

To explore the impact of the potential differences in analysts' ranking decision inputs and forecaster-company interactions, this section also partitions the observations according to whether the issuer of a recommendation is a national brokerage firm, a regional brokerage firm, or a non-brokerage agency. I isolate recommendations made by brokerage and non-brokerage analysts to test the following hypotheses. First, I test whether brokerage (non-brokerage) analyst recommendations are perceived to have greater (poorer) information content. Second, I test whether a more negative signaling

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31 I select linear model (1) over the Sharpe-Lintner CAPM model, or

(1a) $R_{jt} - R_{ft} = \alpha_j + \beta_j (R_{mt} - R_{ft}) + \varepsilon_{jt}$

because of data constraints. Specifically, the proxy measures of risk-free rate, Citibase one-year Treasury Bill returns, are only available for the period of 1961-90. Note that if $(1 - \beta_j) R_{ft}$ is non-trivial *and* non-stationary, model (1) is likely to be less effective in generating abnormal returns than (1a). Nevertheless, potential misspecification of returns generating model does not appear to bias my test results. Adopting Citibase one-year T-Bill rates as a proxy for R_{ft}, I run both long- and short-windowed tests for 1987-88 recommendations using model (1a). The findings are almost identical to the results documented in Sections 4.2, 6.1 and 6.2.

Moreover, test results of this study are robust against the use of alternative market indices as proxies for the aggregate market returns, or R_{mt}. There appear to be similar patterns of abnormal price movements accompanying analyst recommendations for *S & P 500 (Non-S & P) firms* when either equally-weighted market returns or return on the Standard and Poor's composite index (NASDAQ composite return) substitute value-weighted market returns as a proxy for R_{mt}.

effect exists in brokerage-firm analysts' *strong sell* or *sell* recommendations. Moreover, I further partition brokerage-firm recommendations depending on whether national or regional brokerage firms provide them, examining whether there are differential levels of information content and bias between these two groups of recommendations.

4.2.2 EMPIRICAL RESULTS

Table 3 presents evidence on security return behavior immediately surrounding the time of analyst recommendations. It presents the security price reactions to each analyst recommendation category and the results of significance tests, showing that analyst recommendations are perceived to be biased but informative.[32] On the one hand, stock prices behave as if *hold* recommendations are perceived as a negative signal. This table documents significantly negative abnormal price performance for the *hold* portfolio, suggesting that investors discount for expected bias in recommendations.[33] On the other hand, security prices behave as if the levels of analyst recommendations have information content. The t-statistics in Table 3 indicate significant (marginally significant) positive

32 Table 3 reports the results of significance tests adopting beta-adjusted security returns accompanying analyst recommendations to measure the extent investors adjust their beliefs based on analyst recommendations. As specification checks, I also conduct significance tests examining beta-and-size-adjusted returns. I use market value as a proxy for company size and estimate slope coefficients in a cross-sectional short- and long-windowed beta-adjusted returns versus prior-year market value regression models with benchmark period measures. With the coefficient estimates, I then calculate contemporaneous and long-windowed beta-and-size-adjusted returns for each recommendation. The test statistics suggest there exist significantly positive (negative) beta-and-size-adjusted returns for *strong buy* and *buy* (*hold, hold/sell,* and *strong sell*) portfolios. Thus they reconfirm the beta-adjusted return test results.

33 Rational investors should adjust for any known bias and appropriately react to analysts' dropping coverage or delaying the research report issuance. Despite the potential of analysts' strategic reporting, their earnings forecasts and recommendations are still among the major competing sources of information to companies' own financial reports, statements, and announcements. A biased research report is still informative if investors learn to undo the bias. They may trade off the cost of ignoring information provided by forecasters who are likely to be strategic (Type I error) against losses due to accepting the biased reports (Type II error). As an extension to this study, I will conduct the following empirical tests to explore whether investors are rational. First, how do investors react to analysts who consistently issue biased reports? Second, how do investors react to security analysts' "strategic withholding of reports"? Do they view "dropping coverage" as a very negative signal? Would there be pooling equilibrium? How bad would be a firm's condition for the executives' being indifferent as to whether analysts drop the coverage? Would the price reactions to analysts' issuing downward EPS forecast revisions without accompanying recommendations be as negative as those to the reports with *both* negative EPS revisions and unfavorable recommendations? In other words, it tests whether, with the *cooling periods* before security offerings being controlled for, no news (the absence or delay of recommendation ratings) is regarded as bad news?

abnormal price performance for *strong buy* (*buy*) and significantly negative performance for *hold/sell* and *strong sell* portfolios.[34]

Panels B, C, and D of Table 3 document security price reactions accompanying the five levels of analyst recommendations by three different types of analysts (national-brokerage-firm analysts, regional-brokerage-firm analysts, and non-brokerage-agency analysts). Consistently, significance tests of mean abnormal returns reconfirm that analyst recommendations are perceived to be upward biased. *Buy* (*Hold*) recommendations, regardless of the type of information intermediaries, are accompanied by trivial (negative) abnormal returns. Moreover, the recommendations of national and regional brokerage analysts appear to have greater information content than non-brokerage analysts', in spite of the greater potential for bias by brokerage firm analysts.[35] This result is contrary to popular thoughts and consistent with the synergy hypothesis that brokerage firm analysts' incentives and/or opportunities to work closely with client company executives give them an advantage in making recommendations.[36] Furthermore, these panels provide evidence consistent with the hypothesis that national analysts have greater concern for reputation and provide less optimistic recommended lists. On average, national (regional) analysts' favorable recommendations appear to have more (less) pronounced announcement effects. For instance, the mean abnormal returns during [-2, 3] for national brokerage analyst *strong buy* recommendation for *S & P 500 firms* (*Non-S & P firms*) is 0.0057 (0.0142), whereas the mean abnormal returns during [-2, 3] for regional brokerage analyst *strong buy* recommendation for *500 firms* (*Non-S & P firms*) is 0.0031 (0.0123). These findings have significant empirical implication for current research, which prevalently use analysts' prospective estimates, especially non-brokerage analysts' earnings forecasts, to proxy the information set of sophisticated market participants.

34 Also see Figure 1 (Figure 2), which contains the plots of average cumulative beta-adjusted returns from 60 days prior to the recommendation date to 150 days after the recommendation date for *S & P 500 firms* (*Non-S & P firms*) regarding the five recommendation levels. Both figures demonstrate positive (negative) abnormal security returns accompanying the issuance of *strong buy* (*hold, hold/sell,* or *strong sell*) recommendations but insignificant market reactions to *buy* recommendations.

35 Still, there may be individual analysts or specific non-brokerage agencies that potentially have superior access to firm-specific information as well as superior discriminating ability. As an extension to this paper, I will further partition non-brokerage analysts by their major sources of information.

36 This test result suggests that non-brokerage-agency analysts' prospective estimates should be used with caution to proxy the information set of sophisticated market participants *at the recommendation date*. Moreover, these analysts' early dissemination of their findings to preferred subscribers may contribute to the finding.

4.2.3 A SPECIFICATION CHECK FOR CROSS-SECTIONAL CORRELATION

The significance tests reported in Section 4.2.2 may be biased due to cross-sectional correlation in abnormal returns. In particular, the beta-adjusted return measures reported in Panels A, B, C, and D are not independent among observations. First, recommendations may be clustered in time if security analysts update their recommendations in response to common events. Second, even for recommendations that are, say, six trading days apart, there may still exist overlapping cumulating periods in the abnormal return tests, which adopt a [-2,3] event window.

To explore whether clustering in the timing of analysts' investment recommendations affects my conclusions, I conduct sensitivity tests in which all observations are independently distributed through time. Specifically, I partition my sample into two hundred and seven distinct six-day trading periods. While examining *mean* [-1,1] market-model-beta adjusted returns, I exclude recommendations issued on either the first or the last trading day of each six-trading-day period to eliminate any overlapping in event window for abnormal returns.

Panel E of Table 3 presents the results of my specification checks that examine contemporaneous abnormal returns for recommendations issued on the second, the third, the fourth, and the fifth trading days of each period. First, it shows that there exist significantly positive (negative) [-1,1] abnormal returns accompanying *strong buy* (*hold/sell* and *strong sell*) recommendations, suggesting that recommendations are informative. Second, *buy* (*hold*) recommendations appear to induce trivial (significantly negative) abnormal returns, suggesting that recommendations are upward biased. These results are consistent with the findings reported in Panels A, B, C, and D of Table 3. While the t-statistics in Panel E are generally lower, they remain highly significant. Accordingly, the conclusions drawn from Panels A to D are not affected by cross-sectional correlation.[37]

4.2.4 A SPECIFICATION CHECK FOR CONTEMPORANEOUS EARNINGS ANNOUNCEMENTS

This section examines whether the information content of recommendations is due to contemporaneous earnings announcements. The tests in Section 4.2.2 do not control for

[37] Results of tests adopting mean [-1,0] abnormal returns for recommendations issued on the second, the third, and the fourth trading days of each distinctive four-trading-day period are also consistent with the findings reported in Panels A, B, C, and D of Table 3 and are available upon request.

contemporaneous earnings announcements. Therefore, it is possible that the results documented reflect investors' response to contemporaneous announcements such as earnings rather than investors' response to analysts' recommendations. To test for this notion, I partition the observations by whether the recommendation date is within a four-day period surrounding the firm's quarterly earnings announcement.[38] For both partitions, I replicate my Section 4.2.2 significance tests.

Panels F and G of Table 3 present the results. Panel F (Panel G) reports the test statistics for [-2,3] market-model-beta adjusted returns for recommendations issued within (outside) the [-2,1] earnings announcement periods. Statistically significant abnormal returns appear for recommendations that coincide with quarterly earnings announcements and for recommendations outside the earnings announcement periods, suggesting that contemporaneous earnings announcements are not responsible for the results in Panels A, B, C, D, and E.[39]

4.3 ABNORMAL VOLUME ACCOMPANYING ANALYST RECOMMENDATIONS

Motivated by prior research findings that trading volume and the flow of information are correlated, this section examines the statistical significance of abnormal trading volume accompanying recommendations.[40] While we might not detect a significant stock price effect associated with a recommendation if it is interpreted by investors to mean "hold", if significant abnormal volume were documented for each of the five levels of recommendations, it would be consistent with the hypothesis that recommendations have information content ($\mathbf{H_{1a}}$).

4.3.1 RESEARCH DESIGN

I calculate the abnormal trading volume measure, or *AV*, by applying the approach introduced by Ajinkya and Jain (1989) and Barber and Loeffler (1993). A transformation taking natural log of one plus trading volume is performed to obtain a normally distributed explanatory variable. For each security, I estimate the market model for the log transformed trading volume

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38 I retrieve corporate earnings announcement data from COMPUSTAT. Observations with no quarterly earnings announcement dates available are excluded from the samples.

39 Also note that only a small percentage of the observations coincides with quarterly earnings announcements.

40 See, for example, Holthausen and Verecchia (1990) and Grundy and McNichols (1989).

$$V_{jt} = \alpha_j + \beta_j V_{mt} + \varepsilon_{jt}. \quad (2)$$

The exponent of the difference between the actual and the predicted log transformed volume, or AV, measures the ratio of (1 + actual volume) to (1+ predicted volume).[41] I then conduct significance tests of whether AV is greater than 1 during the period surrounding analyst recommendations.

4.3.2 TEST RESULT

Table 4 documents abnormal trading volume over short event windows (Panels A and B) and the fifty-one-trading-day ([-25, 25]) event window (Panel C) surrounding analyst recommendations for each of the five recommendation levels. It reports that the security trading volume of both *S & P 500* and *Non-S & P* test groups increase significantly during the event period of analyst recommendations. Each and every t-test rejects the null hypothesis that AV is less than or equal to one. Consistently, Figure 3 (Figure 4), which contains plots of average market-model adjusted volume associated with analyst recommendations during [-60, 150] for *S & P 500 firms* (*Non-S & P firms*), also shows that the trading activities peak at the recommendation date regardless of the recommendation ranking. These results lend support to the hypothesis that recommendations are timely and important in conveying information.

Table 4 and Figures 3 and 4 also show that *hold/sell* and *strong sell* (*strong buy* and *buy*) portfolios are associated with more (less) pronounced abnormal volume, suggesting heavier flows of information surrounding the release of unfavorable recommendations. This phenomenon may stem from the differential announcement effects between favorable and unfavorable recommendations, as documented in Table 3. Observing the asymmetric distribution of recommendations, and taking into account analysts' incentive to bias up the rankings, investors may regard unfavorable recommendations to be more revealing than favorable recommendations. This phenomenon may also arise if *buy* recommendations are unchallenged, whereas *sell* recommendations, once released, invoke counteractions by company executives and other optimistic analysts.

41 For example, AV =2 means that actual volume is approximately double predicted volume during the event period.

5. Incremental Information Content of Analyst Recommendations, Analyst Earnings Forecast Revisions, and Recommendation Changes

This section explores (1) whether investment recommendations (EPS forecast revisions) are sufficient statistics for the contemporaneous EPS forecast revisions (recommendations), and (2) whether the levels of recommendations are perceived as sufficient statistics for recommendation changes.

5.1 PERCEIVED INFORMATION CONTENT IN EARNINGS FORECAST REVISION (RECOMMENDATION) GIVEN THE CONTEMPORANEOUSLY RELEASED RECOMMENDATION (FORECAST REVISION)

There are several reasons to expect that earnings forecast revisions have *incremental* information content. First, investment recommendations are a coarse measure. Security analysts generally summarize their assessment of a company's management strength, competitive advantage, supply and demand environment, and all other critical aspects with only five rankings. The less frequent usage of the last two ratings, *hold/sell* and *strong sell*, further limits their potential informativeness. Second, analysts rarely specify their investment horizons when making recommendations. Third, analyst *buy/hold/sell* opinions may have different information implications for investors with different levels of risk tolerance or non-trivial transaction costs. As indicated by both the *Survey* and ordered probit analysis results documented in Chapter 1, analysts do not fully adjust for market risk in making recommendations.[42] Furthermore, most analysts do not consider investors' transaction costs in making recommendations.[43] However, investors' attitudes toward risk may deviate from those of the analysts.[44] Fourth, recommendations may be subject to

42 Only 20% of the analysts who participated in the *Survey* stated that they adjust for the risk factor to make a recommendation. Moreover, consistent with the hypothesis that analysts recommend more favorably for securities with greater systematic risk, Chapter 1 documents significantly negative slope coefficient in his ordered probit analyses of recommendation level versus pre-recommendation beta.

43 In the *Survey*, only 1 out of the 43 analyst participants (2.5%) stated that his recommendations are systematic risk and transaction cost adjusted.

44 The notion that investors are heterogeneous towards each specific level of systematic risk is consistent with the phenomenon that many financial products are constructed and kept with differential risk levels. If an analyst does not fully adjust for systematic risk, no matter whether the weights he assigned to the potential factors in making recommendations (e.g., he makes recommendations based on predicted *mean*-adjusted returns) is common knowledge, and no matter whether there is divergence in assessing the company's market risk, the single signal of *buy* or *sell* recommendation is *not* sufficient for the investing public to invert either the sign or the magnitude of beta-adjusted returns measure in his information set.

more upward bias than earnings forecasts.[45] Strategic analysts may be more reluctant to issue unfavorable recommendations, which could more seriously jeopardize their relationships with corporate executives than the level of their EPS forecasts. The investing public, therefore, might need additional signals regarding the company's future earnings stream to facilitate their own assessment tasks.[46]

In contrast, there are also reasons to expect that analyst recommendations provide information *incremental* to earnings forecasts. Above all, accounting earnings may be viewed as measuring underlying economic earnings with error. Companies may have either non-trivial transitory components of earnings or non-trivial components of changes in firm values not recognized by the accounting system. The following reasons explain why measures of change in current and near-future earnings per share (hereafter ΔEPS_t and ΔEPS_{t+s}) may not fully capture the change in future profitability. First, accounting systems may be conservative rather than unbiased in recognizing companies' gains or losses. Second, accounting procedures, which generally focus on operating events, may not fully capture the expected impacts of financing arrangements and investing activities.[47] Third, accounting incomes may not fully reflect expected future gains/losses upon cessation of the firms through takeover, liquidation, or bankruptcy. Therefore, even ΔEPS_t and ΔEPS_{t+s} may be insufficient to capture changes in growth rate for firms which have low earnings persistency (e.g., growing firms), companies with contingent liabilities, companies with substantial marketing or long-term profitability efforts (e.g., companies invested in market capacity, R&D, advertising effects, future competition, goodwill, and market shares).

Because of the gap between accounting and economic earnings, even those analysts who can accurately forecast the permanent component of a company's future earnings may not fully reveal their expected changes in its firm value through revisions of current- and subsequent-year earnings forecasts. In settings in which forecasting agencies and financial press adopt forecast accuracy as a major variable in evaluating analysts' performance, security analysts' optimal forecast strategy is to tailor their earnings and earnings growth rate estimates to the anticipated GAAP-based numbers, instead of the

45 See Lin and McNichols (1993a), Lin and McNichols (1993b), and Lin (1993b).

46 Both reported accounting earnings and analyst earnings forecast have these potential desirable attributes in supporting investment decisions.

47 As an example, accounting incomes do not incorporate potential tax benefits due to firms' increases in leverage ratios.

estimated economic profits, to reduce the difference between reported and estimated earnings measures, or the *forecast error*. As a consequence, investors may gain from further observing analysts' investment recommendations, which may reflect analysts' interpretations of concurrent valuation-relevant information beyond accounting earnings.

Most prior studies related to analyst earnings forecasts do not isolate the abnormal price impacts of analyst earnings forecasts and investment recommendations. However, price movements accompanying analyst forecasts may reflect market reactions to simultaneously released *buy/hold/sell* recommendations and analyses concerning specific operating or financing activities. Without controlling for the incremental announcement effects of these signals, regression tests examining analyst earnings forecasts may be confounded.

In contrast, this section explores the *incremental* information content of these two summary signals. Contributions of isolating the price impacts reach beyond mitigating potential confounding problems. By documenting whether EPS estimates (recommendations) are sufficient statistics for valuation relative to contemporaneously released recommendations (EPS estimates), this study helps demonstrate investors' information inputs and provides an explanation to analysts' forecasting earnings as well as making investment recommendations.

5.2 THE INFORMATION CONTENT OF RECOMMENDATION CHANGES[48]

This section also investigates whether security price movements behave as if the change in recommendation rating is perceived to be informative given the level of analyst recommendation, discriminating among hypothesized social norms related to the information conveyed by recommendation changes.[49]

The first norm is that the magnitude and the direction of recommendation changes are incrementally informative. It could arise through the following mechanism:

> Analysts reveal their expectation through both recommendation levels and changes. It may partly stem from their reluctance to make dramatic (multiple-

48 If recommendation changes have incremental information content, a descriptive model for the association between analyst opinions and fundamental variables would need to be multivariate.

49 In an extension to this study, I will further partition the sample by the direction of rating change and examine absolute price changes and abnormal trading volume accompanying recommendation changes, investigating whether down-grading changes are perceived to be more informative than upgrading ones.

level) down-grading recommendation changes.[50] Instead, analysts use rankings and ranking changes jointly to reveal their assessments. In other words, if analysts were non-strategic, they would issue more unfavorable ratings. In response, investors may perceive down-grading (up-grading) rating changes to have negative (positive) information implications over and above the rating levels.

This hypothesis predicts that analysts' down-grading changes from *buy* recommendations to *hold* recommendations or their "*reiterating hold recommendations*" may have a more negative signaling effect than upgrading a recommendation from *sell* to *hold.*

Two alternative hypotheses predict that investors would not gain from trading on the magnitude or the direction of recommendation changes: (1) analysts behave non-strategically, and (2) analysts behave strategically in making recommendations, but they, and therefore investors, do not regard recommendation changes as being *incrementally* informative. These alternative types of social norms suffice to predict that levels of analyst recommendations are sufficient statistics for recommendation changes. For example, analysts' lowering a company's rating from *strong buy* to *buy* should have the same signaling effect as their up-grading a company's rating from *sell* to *buy.*

5.3 RESEARCH DESIGN AND TEST RESULTS

To test whether investment recommendations (earnings forecast revisions) are sufficient statistics for the contemporaneous earnings forecast revisions (recommendations), as well as whether recommendation changes provide *incremental* information to the market, regression models

$$CAR = \beta_0 + \beta_1\ Rev + \varepsilon_3 \qquad (3),$$
$$CAR = \beta_0 + \beta_1\ Rec + \varepsilon_4 \qquad (4),$$
$$CAR = \beta_0 + \beta_1\ Rec + \beta_2\ ChgRec + \varepsilon_5 \qquad (5), \text{ and}$$
$$CAR = \beta_0 + \beta_1\ Rec + \beta_2\ ChgRec + \beta_3\ Rev + \varepsilon_6 \qquad (6)$$

are estimated for both *S & P 500* and *Non-S & P* test groups over event windows [0,3], [-1,0], [-1,1], and [-2,2].[51] For these models, (1) *CAR* denotes market-model-beta-adjusted

50 Regardless of the cause, such hypothesized strategic conduct suffices that the direction of analyst recommendation revisions have information content.

51 This paper only presents coefficient estimates and test statistics of the regression analyses using [-1,0] event window because of their robustness against adopting alternative windows ([0,3], [-1,1] and [-2,2]).

returns cumulated over the event window, (2) *Rec* denotes the level of investment recommendation. *Rec* takes the value of -2 when analyst recommends *strong buy*; *Rec* =-1 means *Buy*; *Rec* = 0 means *hold*; *Rec* = 1 means *hold/sell*; *Rec* = 2 means *strong sell*, (3) *ChgRec* denotes the current recommendation rating less the most recent rating, and (4) *Rev* is defined as analysts' current earnings forecast less the most recent forecast, deflated by the closing price five trading days prior to the estimate date of the previous forecast.[52] By examining both t-statistics for estimates of the slope coefficients and differences in estimated adjusted-R^2 measures among the regression equations, I explore whether analysts' forecast revisions, recommendation ratings, and recommendation change provide *incremental* information.[53]

Moreover, for *S & P 500* observations, since there are a large number of sample observations. I also estimate the regression with dummy variables to examine whether each level is regarded as significantly more favorable than the next level. For these observations, rather than including *Rec* with values from -2 to 2, I use dummy variables *L1*, *L2*, *L3* and *L4* to collectively represent the recommendation levels. Regression models

$$CAR = \beta_0 + \beta_1 \, Rev + \varepsilon_7 \qquad (7),$$

$$CAR = \beta_0 + \Sigma_{i=1,4} \, \beta_{Li} \, Li + \varepsilon_8 \qquad (8),$$

$$CAR = \beta_0 + \Sigma_{i=1,4} \, \beta_{Li} \, Li + \beta_2 \, ChgRec + \varepsilon_9 \qquad (9), \text{ and}$$

$$CAR = \beta_0 + \Sigma_{i=1,4} \, \beta_{Li} \, Li + \beta_2 \, ChgRec + \beta_3 \, Rev + \varepsilon_{10} \qquad (10)$$

are estimated over event windows [-2,3], [-2,2], [-1,0] and [0,3]. For these models, vector [*L1*, *L2*, *L3*, *L4*] is set to be equal to [1, 1, 1, 1] if the security is given a *strong buy* recommendation; [*L1*, *L2*, *L3*, *L4*] = [0, 1, 1, 1] represents *buy*; [*L1*, *L2*, *L3*, *L4*] = [0, 0, 1, 1] represents *hold*; [*L1*, *L2*, *L3*, *L4*] = [0, 0, 0, 1] represents *hold/sell*; [*L1*, *L2*, *L3*, *L4*] = [0, 0, 0, 0] represents *strong sell*.[54] If investors perceive a given recommendation level *j*

[52] Results of tests with this specification are robust against adopting an alternative deflator. This paper only presents findings of the tests using price-deflated forecast revisions. Nevertheless, results of my sensitivity tests, which define an analyst EPS forecast revision as analyst's EPS estimate less the most recent EPS forecast made by any analyst and lead to similar conclusions, are available upon request.

53 As an extension, I will further partition observations by the recommendations ranking and observe the influence of analyst forecast revisions within each ranking group.

[54] With large samples, the dummy variable research design, which does not require that analyst recommendations have linear impacts on abnormal returns, is more powerful than models (3) to (6). Note that *ex ante* it is not clear whether, say, the difference in abnormal returns accompanying *strong buy* versus *buy* is the same as *hold/sell* versus *strong sell*.

to be significantly more favorable than level $j + 1$, then estimates for slope coefficient β_{Lj} would be significantly positive.

5.3.1 INCREMENTAL INFORMATION CONTENT IN EARNINGS FORECAST REVISIONS AND RECOMMENDATIONS

Consistent with $\mathbf{H_{2a}}$, Table 5 reports that analyst forecast revisions and recommendations are both regarded as having information content. Security prices behave as if investors trade on both analyst recommendations and analyst forecast revisions. The results also indicate that the impact on security market returns is much stronger for analyst recommendations than EPS forecast revisions.

Panels A-1, B-1, and C-1 of Table 5 show that both current-year earnings forecast revisions (hereafter Fy1) and subsequent-year earnings forecast revisions (hereafter Fy2) have explanatory power for abnormal security price performance accompanying the release of analysts' research reports.[55] Panels A-4, B-4, and C-4 of Table 5 indicate that when the correlation between Rec and Fy1 is attributed to recommendation, Fy1 still has power in explaining for contemporaneous abnormal returns for both *S & P 500* and *Non-S & P* test groups.[56] The inclusion of Fy1 in the regression model increases the adjusted-R^2 measures.[57]

Table 5 also shows that, when the correlation between Rec and Fy2 is attributed to Rec, Fy2 has more pronounced power in explaining the variation of contemporary cumulative abnormal returns than Fy1. The inclusion of Fy2 in the regression model helps increase the adjusted-R^2 measures for all short-window tests (all except the test with [-2,2] event window) for *S & P 500 firms* (*Non-S & P* firms). The finding that Fy2

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55 The results shown in Panels A-1, A-2, B-1, B-2, C-1, and C-2 are robust with respect to Spearman rank correlation checks.

56 My sensitivity analysis results indicate that when the correlation between Rec and Fy1 is attributed to Rec, Fy1 has (has no) power in explaining for abnormal returns cumulated over event period [-2,2] ([0,3]) for both *S & P 500* and *Non-S & P* test groups.

The finding that Fy1 does not help explain the abnormal price movement over [0,3] for *S & P 500 firms* is consistent with Beneish (1990), who documents that stock prices adjust prior to publication of earnings forecasts. One potential explanation is that analysts tend to disseminate their findings to preferred clients or subscribers before the *research report date.*

57 Note that despite the existence of noise in the revision measures caused by factors such as differential definitions for EPS among different analysts, the inclusion of forecast revision in the regression model still increases the adjusted-R^2 measures.

outperforms Fy1 in conveying incremental information, especially for *S & P 500 firms*, is consistent with the notion that Fy2 reflects relatively more (less) of the permanent (transitory) component of earnings.[58]

A particularly striking feature of the multiple regression results reported in Table 5 is the finding that analyst recommendations are considerably more informative than analyst forecast revisions.[59] In each and every market reaction test, the slope coefficient estimate for the level of recommendation remains significantly negative.[60] Moreover, the t-test results can be reconfirmed by examining the adjusted-R^2 measures, which suggest that even when the correlation between Rec and Fy1 (Fy2) is attributed to Fy1 (Fy2), Rec has consistently significant power in explaining the variation of contemporaneous security price changes.[61]

Panels B and C show that tests of models (7), (8), (9) and (10) provide consistent results. First, the findings suggest that variation of contemporaneous abnormal returns cannot be fully explained by investment recommendations. Investors appear to perceive Fy1 and Fy2 revisions to be incrementally informative. Second, when the correlation between recommendation and Fy1 (Fy2) revision is attributed to Fy1 (Fy2), an analyst recommendation appears to be a significantly more positive signal than recommendations of a less favorable level. T-statistics shown in Panel B suggest that estimates for β_{Lj} coefficients are all significantly positive for observations with current-year forecast revisions available. In addition, for observations with subsequent-year forecast revisions available, despite the small sample size, significance test results in Panel C are consistent with the notion that the market perceives (1) *strong buy* and *buy* as more favorable rankings than *hold* and (2) *hold* and *hold/sell* as more favorable rankings than *strong sell*.

Finally, the returns versus recommendation regression test results presented in Table 5 also confirm the findings in Section 4 that the market regards analyst investment

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58 There also exist two competing explanations. First, as Watts and Zimmerman (1986) note, executives of large firms are likely to choose accounting procedures that defer reported earnings to future periods. Second, accounting earnings estimates may reflect economic earnings with a time lag.

59 This finding is robust against specification checks for both event window selection and deflator for earnings forecast revision.

60 Recall that the most favorable recommendation is coded 1 and the most unfavorable one is coded 5, consistent with industry practice.

61 Also, Panel A of Table 5 demonstrates that the slope coefficient estimate for the level of recommendation is significantly negative in every simple linear regression test of market price reaction, suggesting that the market responds positively to favorable recommendations.

recommendations as being upward biased. Consistent with the hypothesis that *hold* is perceived as an unfavorable signal, Panel A-1 reports that, for recommendations released together with current-year earnings forecasts, the intercept estimate of the regression test is significantly negative.[62]

5.3.2 INCREMENTAL INFORMATION CONTENT IN RECOMMENDATION CHANGES

Panels A-3, B-3, and C-3 of Table 5 indicate a difference in the levels of significance for information content in recommendation changes between *S & P 500* and *Non-S & P firms*. For *S & P 500 firms*, controlling for stock market reactions to recommendations, I find weak evidence that recommendation changes have incremental information content. Consistent with $\mathbf{H_{2b}}$, the inclusion of *ChgRec* in the regression model increases the adjusted-R^2 measures. In contrast, for *Non-S & P firms*, controlling for stock market reactions to recommendations, I find that recommendation changes have no significant power in explaining the contemporary abnormal price changes.

6. *Analysts' Actual Rating Performance and Post-Recommendation Drifts*

6.1 ANALYSTS' PERFORMANCE IN SELECTING STOCKS

This section examines the cumulative market-model-beta-adjusted returns during the first 150 trading days subsequent to the announcements of recommendations (hereafter CAR[0,150]) to explore analysts' performance in making unfavorable, favorable and *hold* recommendations.[63] During the 73-month test period (July 1987 -- July 1993), security analysts' unfavorable (favorable) recommendations appear to have more (less) pronounced discriminating success.[64] Moreover, analysts' *hold* recommendations appear to be a euphemism for *sell*.

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62 This test thus controls for contemporaneously disclosed earnings forecasts. Note that analyst's *hold* ratings are coded "0" in these regressions. Significantly negative intercept coefficients indicate a negative price reaction to analysts' *hold* recommendations.

63 I also provide statistics for cumulative abnormal returns during [0, 60] to demonstrate medium-term gains or losses of portfolios formed based on recommendation rankings. Furthermore, I conduct sensitivity analyses to examine the robustness of test results in this section against different event window specifications. The results of tests using window [-2, 150] ([-2, 60]), which are similar to those using [0, 150] ([0, 60]), are available upon request.

64 Note that potentially analysts' unfavorable (favorable) recommendations may be more (less) revealing. Therefore, instead of examining cumulative abnormal returns of a single investment portfolio created by buying (short selling) one share of each of the securities for which analyst recommend *buy* or *strong buy* (*hold/sell* or *strong sell*, respectively) this study examines signs and

6.1.1 ANALYSTS' *STRONG SELL* AND *HOLD/SELL* RECOMMENDATIONS

Panel A of Table 6 shows that the average CAR[0,150] is significantly negative for all brokerage-firm analysts' unfavorable recommendations. It also demonstrates that CAR[0,150] for non-brokerage analysts' unfavorable recommendations for *S & P 500 firms* (*Non-S & P firms*) are significantly negative (negative but statistically insignificant). On average, investors with trivial transaction costs and a short position in securities receiving *sell* or *strong sell* would have earned an abnormal return of approximately 2.3% (12%) over the 150 trading days following the recommendation date, or an annualized abnormal return of approximately 3.9% (20%) for *S & P 500* (*Non-S & P*) *firms*.

6.1.2 ANALYSTS' *STRONG BUY* AND *BUY* RECOMMENDATIONS

Panel A of Table 6 also demonstrates that among the 12 portfolios of securities on analysts' recommended lists, national and regional brokerage analysts' *strong buy* for *S & P 500 firms* are the only two portfolios with significantly positive mean CAR [0,150]. The average CAR[0,150] following national (regional) brokerage analysts' *strong buy* recommendations for *S & P 500* is 0.014 (0.007) and is significantly greater than zero. However, this finding lends support to the hypothesis that analyst *buy* recommendations are a euphemism for *hold*. For all the *buy* portfolios for *S & P 500 firms*, CAR[0,150] is not significantly different from zero. Furthermore, consistent with the synergy hypothesis, non-brokerage analysts' *strong buy* (*buy*) recommendations appear to be followed by significantly negative (negative but statistically insignificant) long-window abnormal returns. On the other hand, for *Non-S & P firms*, analysts do not appear to have superior skills in predicting their long-term revaluation. All portfolios that are on these analysts' recommended lists have significantly negative mean CAR[0,150] regardless of the type of information intermediaries.[65]

6.1.3 ANALYSTS' *HOLD* RECOMMENDATIONS

The test result also provides weak evidence of optimism, suggesting one may realize greater (less) returns by a simple trading strategy that short-sells (holds) specific subsets of

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significance of potential abnormal buying (selling) gains for each of the five levels of recommendations.

65 The finding that analysts consistently performed poorly in making *buy* recommendations for *Non-S & P firms* is puzzling. But it is robust with respect to specification checks with alternative benchmark periods for estimating beta and alternative market model indices.

securities analysts recommend to *hold.* Table 6 shows that (1) for *Non-S & P,* the mean CAR[0.150] measures for *hold* portfolios are all significantly negative, and (2) for *S & P 500,* national-brokerage and non-brokerage analysts' (regional analysts') *hold* portfolios yield trivial (significantly negative) CAR[0.150].

6.2 ABNORMAL RETURNS DURING THE POST-ANNOUNCEMENT PERIOD

As shown in Table 6 and Figures 1, 2, 5 and 6, investors appear to under-react (over-react) to analysts' favorable (unfavorable) recommendations upon their issuance.[66] With respect to the overall sample, analysts' favorable (unfavorable) recommendations are followed by positive (negative) short-term abnormal returns. However, the patterns of subsequent abnormal returns indicate that market prices fail to appropriately reflect the implications of analyst recommendations.[67]

First, the initial abnormal return performance associated with favorable recommendations is subsequently reversed. The two panels of Table 6 collectively demonstrate that, among the 12 portfolios created based on analysts' recommended lists, the portfolio for national brokerage analysts' *strong buy* recommendations for *S & P 500 firms* is the only group that has non-negative mean CAR[61,150].[68] Consistently, the plots of average cumulative beta-adjusted returns regarding the five recommendation levels shown in Figures 1 and 2 show that, *for the overall samples*, the positive abnormal return following *strong buy* and *buy* recommendations are mostly reversed by trading day 150. The documented large initial market reactions and subsequent price reversals suggest that the investing public, who appear to adjust, at least partially, for expected bias in analyst *hold* recommendations, may still be misled by favorable recommendations.

66 Figures 5 and 6 present the differences between mean dividend-adjusted (raw) returns of the portfolios constructed based on analyst recommendations and expected returns from a portfolio that generate the value-weighted market returns from 60 days prior to the recommendation date to 150 days after the recommendation date. These figures demonstrate how analysts performed in both selecting stocks and *timing the market* during the test period.

67 This study focuses on exploring whether the perceived informativeness of analysts' recommendations and the extent of competing signals account for investors' over- or under-reactions to recommendations. Nevertheless, this anomaly may also be due to potential omitted factors, including omitted risk measurements other than market-model beta, as well as market imperfection such as taxes and transaction costs. Furthermore, because of the short test period, it may be difficult to make strong inferences as to the extent the market is informationally efficient.

68 It is a subjective matter whether such a [61, 150] event window outperforms any other potential selections. However, the statistical test results of over- and under-reactions are consistent with the patterns shown in Figures 1 and 2.

Second, the investing public appears to only partially react to unfavorable recommendations. Panels A and B of Table 6 and Figures 1 and 2 also show that the mean CAR[61,150] measures are unanimously negative for all *strong sell* and *hold/sell* portfolios. Following the recommendation date, estimated cumulative abnormal returns continue to drift down for these securities. Also, the plots of average market-indices-adjusted returns presented in Figures 5 and 6 lend support for the findings regarding both favorable and unfavorable recommendations.[69]

Additional tests fail to support the notion that research design inadequacy in selecting the benchmark period for estimating beta explains this anomaly.[70] Sensitivity tests using three alternative periods ([-500,-250] U [340,464], [-375,-125] U [340,464] and [-375,-125] U [215,339]) for estimating systematic risk provide (1) similar short-window results, and (2) slightly less pronounced long-window results, suggesting the sample companies are not likely to have experienced significant structural change during the test period.[71] The findings indicate no corroborative evidence that my benchmark period selection, [-500,-250] U [215,339], introduces bias.[72]

6.3 THE INFLUENCE OF COMPETING INFORMATION ON THE MAGNITUDE OF INVESTORS' OVER- OR UNDER-REACTIONS

Sections 6.3 and 6.4 adopt post-recommendation abnormal returns CAR[4,150] and CAR[61,150] to measure the extent of investors' response after the release of

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69 Also, see Figure 7 (Figure 8) for the plots of raw returns (capital gains plus dividends) from 60 days prior to the recommendation date to 150 days after the recommendation date for *S & P 500 firms* (*Non-S & P firms*) regarding the five recommendation levels.

70 The primary objective of these specification checks is to explore the robustness of my long-event-window test results. However, the results of my short-event-window tests are also found to be robust.

71 The failure of beta shifts to explain the observed abnormal price performance can be reconfirmed by examining Figures 5 and 6. These figures demonstrate that, when each and every security is assumed to have the market beta, there are (1) similar patterns of short-term abnormal price performance and (2) similar long-term abnormal price performance for *strong sell* and *hold/sell* portfolios. *For the test period adopted in this study*, results of these tests are not sensitive to changes in the estimates of beta.

72 There is another potential explanation that can not plausibly be reconciled with the specifics in this study. Prior abnormal returns studies have argued that the past estimate of beta can be systematically biased. For example, Ball and Kothari (1989) demonstrate that extreme performance over a 5-year period is likely to be associated with changes in a stock's relative risk, with loser's risk increasing and winner's decreasing. However, note that I define the benchmark period for estimating beta as the union of [-500, -250] and [215, 339].

recommendations. The hypotheses that (1) the magnitude of market under- or over-reactions to an analyst recommendation decreases with the richness of the company's regular information flows (**H_{3a}**), (2) the magnitude of over-reactions to favorable recommendations increases with the perceived information content of the signals (**H_{3b}**), and (3) the magnitude of delayed price response to unfavorable recommendations increases with the richness of counteracting information (**H_{3c}**), are tested by estimating the following model,

$$CARPOSTREC = \zeta_0 + \zeta_1\, SPCODE + \zeta_2\, TA + \zeta_3\, AV + \varepsilon_{11} \qquad (11),$$

where I define *CARPOSTREC* as the cumulative beta-adjusted returns during the post-recommendation period [4,150] or [61,150]. To explore the robustness of the tests, I use both post-recommendation excess return measures as proxies for the magnitude of over- or under-reaction. The dummy variable *SPCODE* takes the value of 1 (0) if the company is (is not) an *S & P 500* company. *TA*, which denotes the concurrent year-end total asset of the company, is a proxy for the quantity of regular information flows. Finally, *AV*, abnormal trading volume surrounding the recommendation date, is used as a proxy for contemporary information flow.[73] The abnormal trading volume measure can reflect the extent to which information is initially impounded in price. For unfavorable recommendations, it has been argued that counteracting signals are likely to account for a substantial proportion of the information flows surrounding the release of analyst recommendation. On the other hand, for favorable recommendations, which are often unchallenged, contemporary information flows are likely to unambiguously reflect the announcement effects of these signals.

Table 7 presents the result of this analysis. It reports that when the effects of other variables are controlled, post-recommendation abnormal returns increase with company size and decrease with abnormal trading volume, regardless of rankings or the event windows for excess returns, indicating that the greater the normal quantity of information flow (the heavier the information flow surrounding the release of recommendations), the less (greater) the magnitude of over- or under-reactions. My proposed explanation for this finding is that (1) investors can more appropriately respond to analyst recommendations when there is more frequent disclosure of information regarding the company, (2) for *BUY* portfolios, the announcement effects may be greater the richer the perceived information

[73] The event window for *AV*, abnormal trading volume, is defined as 51 trading days centered around the recommendation date.

content of these recommendations, (3) for *SELL* portfolios, potential counteracting signals invoked by unfavorable rankings may contribute to under-reactions.[74]

6.4 IS THE MAGNITUDE OF OVER- OR UNDER-REACTIONS DIFFERENT FOR RECOMMENDATIONS PROVIDED BY DIFFERENT TYPES OF INFORMATION INTERMEDIARIES?

This section explores whether the type of agency an analyst belongs to corresponds to post-recommendation drifts. Specifically, I investigate whether investors are less likely to under- (over-) react to unfavorable (favorable) recommendations provided by brokerage (national brokerage) analysts as opposed to non-brokerage (regional brokerage) analysts by estimating pooled regression models,

$$CARPOSTREC = \vartheta_0 + \vartheta_1\, SPCODE + \vartheta_2\, TA + \vartheta_3\, NATCODE + \varepsilon_{12} \qquad (12), \text{ and}$$
$$CARPOSTREC = \lambda_0 + \lambda_1\, SPCODE + \lambda_2\, TA + \lambda_3\, BROCODE + \varepsilon_{13} \qquad (13)$$

where *CARPOSTREC* is defined as the cumulative beta-adjusted returns during the period [4,150] or [61,150]. The dummy variable *SPCODE* takes the value of 1 (0) if the company is (is not) a *S & P 500* company. *TA*, which denotes the concurrent year-end total asset of the company, is a control variable for company size. The dummy variable *BROCODE* takes the value of 1 (0) if the recommendation is issued by a brokerage (non-brokerage) firm. The dummy variable *NATCODE* takes the value of 1 (0) if the recommendation is (is not) issued by a national brokerage firm.

This section avoids making inferences by merely comparing the inter-group difference in CAR[4,150] or CAR[61,150] among the portfolios, an obvious research design. Consistently, preliminary results in Tables 3 and 6 demonstrate (1) less (more) pronounced market price reversals for national (regional) brokerage analysts' favorable recommendations, and (2) less (more) pronounced market under-reactions to brokerage (non-brokerage) analysts' unfavorable recommendations. However, note that small local companies are less (more) likely to be covered by national (regional) brokerage analysts. Differences in magnitude of over- or under-reactions among recommendations provided by national brokerage firms, regional brokerage firms and non-brokerage agencies may result from the differential characteristics of the securities instead of the characteristics of the information intermediaries. Without controlling for company size and S & P 500

[74] The finding is consistent with the notion that large firms have greater post-recommendation returns -- less reversal of favorable rankings and less drift for unfavorable rankings.

membership, which are proxies for the corporate executive's power of being a major supplier of company-specific information, the richness of financial information from other sources, and the market liquidity of the security, the tests may be confounded.

Table 8 provides evidence on differences in post-announcement drifts for different types of information intermediaries (e.g. national-brokerage-firm, regional-brokerage-firm, or non-brokerage-agency). Panels A and B of this table report that national brokerage analysts' recommended lists have superior discriminating ability for longer term performance and are less misleading. Controlling for the effect of company size and Standard and Poor's 500 membership does not alter the result that the excess returns from trading day 61 to day 150 (Panel A) and excess returns from day 4 to day 150 (Panel B) for *strong buy* or *buy* recommendations are marginally greater when the analyst belongs to a national instead of a regional brokerage firm.

Moreover, Panel C (Panel D) of Table 8 shows that the post-announcement abnormal returns from trading day 61 (day 4) to day 150 for unfavorable recommendations are marginally greater when the analyst belongs to a brokerage firm instead of a non-brokerage firm. The finding provides weak evidence in support of the hypothesis that brokerage analysts' unfavorable recommendations are perceived as more negative signals and thus have stronger announcement effects.

6.5 EVIDENCE AGAINST COMPETING EXPLANATIONS TO UNDER- OR OVER-REACTIONS

This study provides evidence against the following three competing explanations for investors' under- or over-reactions. First, test results reported in Table 8 are inconsistent with the notion that brokerage firms' strength of sales force contributes to over-reactions to favorable recommendations. Panels A and B demonstrate less (more) pronounced price reversals regarding securities recommended by national (regional) brokerage-firms, which are likely to have greater (less) sales force strength. Moreover, Panels C and D demonstrate that security price reversals subsequent to brokerage (non-brokerage) analysts' favorable recommendations are not more (not less) pronounced.

Second, investors' under-reactions to unfavorable recommendations are not likely to be driven by insufficient liquidity of the securities. If insufficient liquidity leads to delayed price response, the level of abnormal volume would peak at the recommendation date and then *gradually* decline, with substantial *AV* persisting until the market price is fully adjusted. However, inconsistent findings for both *S & P 500* and *Non-S & P* test groups are indicated in Figures 1, 2, 3 and 4. Despite the fact that cumulative abnormal returns of *strong sell* and *hold/sell* portfolios drift downward throughout the 150 trading days following recommendations, abnormal volume peak at the announcement date and decline immediately afterwards.

Third, the finding does not support the notion that greater (less) publicity of analysts' favorable (unfavorable) recommendations results in investors' over- (under-) reactions. For both *S & P 500* and *Non-S & P* test groups, as shown in Table 4, abnormal volume, which proxy the level of information flows accompanying the release of recommendations, appear to be more (less) pronounced for *strong sell* and *sell* (*strong buy* and *buy*) portfolios. Moreover, the magnitude of market overreaction to favorable recommendations does not appear to increase with the level of publicity of recommendation announcement. As shown in Tables 7 and 8, investors' overreactions are not more (less) pronounced regarding recommendations for larger (smaller) firms, for which analysts' recommendations are likely to be more (less) heavily publicized.[75]

7. Conclusions and Extensions

This study contributes to the contemporary accounting literature by providing a systematic and broad-based investigation of information content and sufficiency in analysts' recommendations and earnings forecasts. This is the first study to examine contemporaneous abnormal returns and volume to investigate how investors perceive analyst recommendations. Moreover, its evidence on whether and when investors would over- or under-react to recommendations helps enrich the contemporary literature of market irregularities.

7.1 INFORMATION CONTENT AND POTENTIAL BIAS IN RECOMMENDATIONS

This study explores both potential bias and perceived information content in recommendations. First, it demonstrates that analysts' unfavorable recommendations are infrequently released. This tendency further limits analysts' ability to convey their findings to the public through their investment recommendations, which are already a coarse signal. Second, it provides evidence consistent with the hypothesis that analyst recommendations are upward biased. *Hold* recommendations are found to be perceived as a euphemism to *sell*. Also, long-term price performance behaves as if *buy* (*hold*) recommendations are a euphemism for *hold* (*sell*), and thus *strong buy* is the singular ranking for positive price performance predictions. Third, it documents that for the aggregate sample, analyst recommendations are perceived as informative. Among investment recommendations,

75 This test uses *TA* and S & P 500 membership as proxies for the level of publicity of recommendations.

contrary to popular thoughts, non-brokerage analysts' ranking signals are perceived to be substantially less informative than brokerage-firm analysts'.

However, this study does not exhaust the potential variables that may be applied to partition information intermediaries or analysts. An extension to this study could be identifying other proxies for analysts' sources of information or sources of conflicting pressure.[76] Future research work may also focus on exploring statistical properties of recommendations offered by specific subsets of analysts, say, the 1993 Wall Street Journal *All-Star* stock pickers or market timers.[77]

7.2 INFORMATION CONTENT IN EPS FORECASTS AND RECOMMENDATIONS

Findings in this study also lend support to the hypothesis that investors form their buying or selling strategies based on both analyst recommendations and analyst earnings forecasts. When the correlation between investment recommendation and EPS forecast revisions is attributed to recommendations (forecast revisions), forecast revisions (recommendations) still appear to help explain the variation of contemporary security price changes. The finding that forecast revisions are not sufficient statistics for recommendations is consistent with the notion that accounting earnings may be viewed as measuring underlying economic earnings with error, especially for companies with substantial transitory components. In contrast, potential factors that EPS forecast revisions have *incremental* information content include analysts' vagueness in specifying investment horizons, investors' heterogeneous levels of tolerance toward risk, investors' non-trivial differences in transaction costs, and perceived optimism in recommendations.

The findings suggest that future research work using analyst reports to further explore investors' financial information inputs is warranted. To start with, researchers can investigate how each of the potential factors contributes to the perceived importance of EPS forecast revisions

7.3 INVESTORS' OVER- OR UNDER-REACTIONS TO RECOMMENDATIONS

Finally, this study documents that security prices behave as if the market over-reacts (under-reacts) to favorable (unfavorable) recommendations. This test result is robust with

76 For example, analyst recommendations may be partitioned by difference in forecasting agencies' compensation schemes. As reported by Dorfman (1991) in his *Heard on the Street* column, compensation packages are substantially heterogeneous among brokerage firms.

77 See Dorfman (1993c) for the lists of analysts and information intermediaries. However, note that studies related to these subsets of analysts, may be subject to survivorship bias.

respect to alternative returns generating model, benchmark periods for estimating beta, and measures for aggregate market returns. Moreover, this study provides evidence against the competing notion that differential strengths of sales forces, differential liquidity of securities, or differential levels of publicity may account for post-recommendation price drifts or price reversals. On the other hand, this study presents evidence consistent with the hypothesis that (1) the magnitude of market under- or over-reactions to a recommendation decreases with the level of richness of the company's regular information flows, (2) the magnitude of investors' over-reactions to favorable recommendations increases with the perceived information content of the signals, and (3) the magnitude of delayed price response to unfavorable recommendations increases with the richness of counteracting information. Furthermore, investors appear to be less likely to under- (over-) react to unfavorable (favorable) recommendations provided by brokerage (national brokerage) as opposed to non-brokerage (regional brokerage) analysts.

This study does not aim to exhaustively cover all the potential reasons that market prices fail to appropriately reflect the future prospect implications of analyst recommendations. An extension to this study could explore other potential factors, investigating how exclusion of risk measurements other than beta, market imperfection such as taxes and transaction costs, and event window specification may help to explain the findings.[78]

78 For instance, if the contrarian market hypothesis is descriptive, the *long* event window ([0, 150]) adopted in this study would be inadequate. In the belief that the market *systematically* overreacts to information, investors who follow contrarian investment strategy would take a long position in extreme losing stocks and anticipate price reversals in as long as five years.

Figure 1

Abnormal Returns Accompanying Analyst
Recommendations on S & P 500 Firms

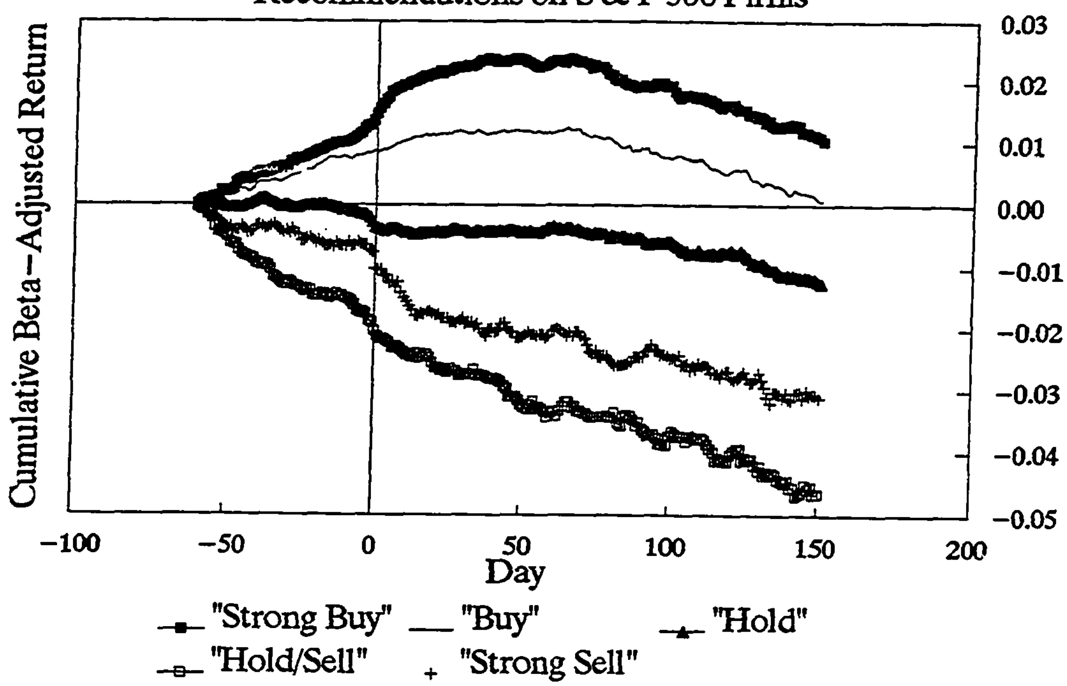

Figure 2

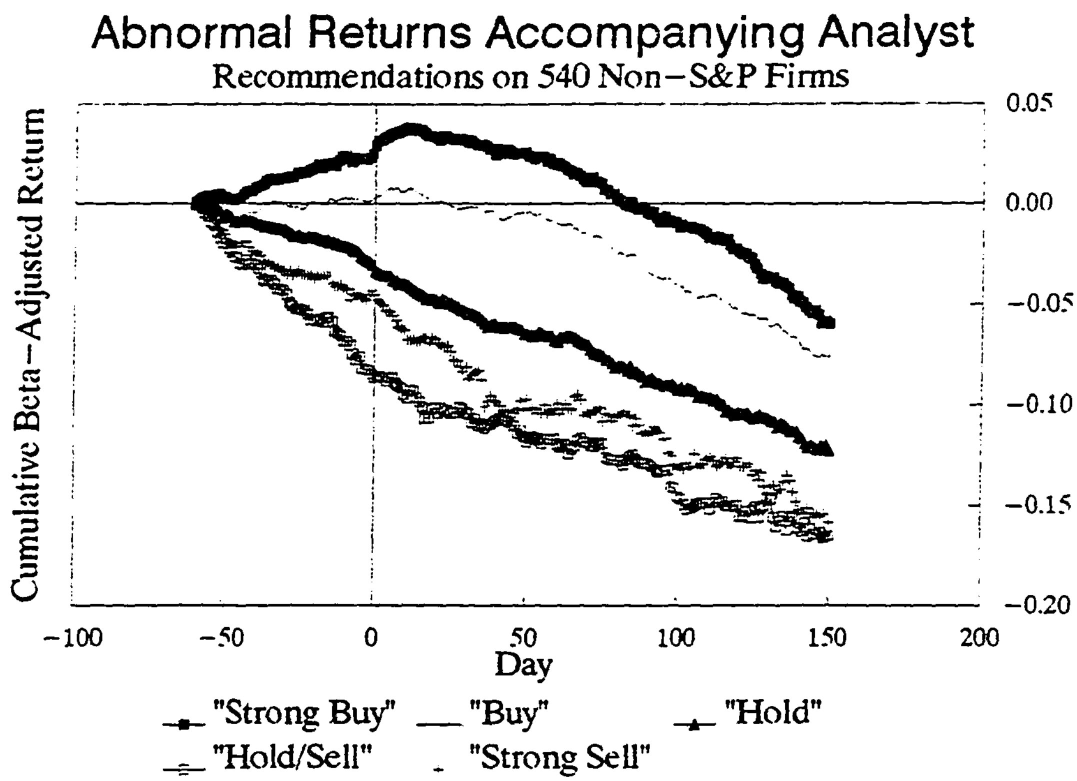
Abnormal Returns Accompanying Analyst
Recommendations on 540 Non−S&P Firms
Cumulative Beta−Adjusted Return
0.05
0.00
−0.05
−0.10
−0.15
−0.20
−100
−50
0
50
100
150
200
Day
"Strong Buy"
"Buy"
"Hold"
"Hold/Sell"
"Strong Sell"

Figure 3

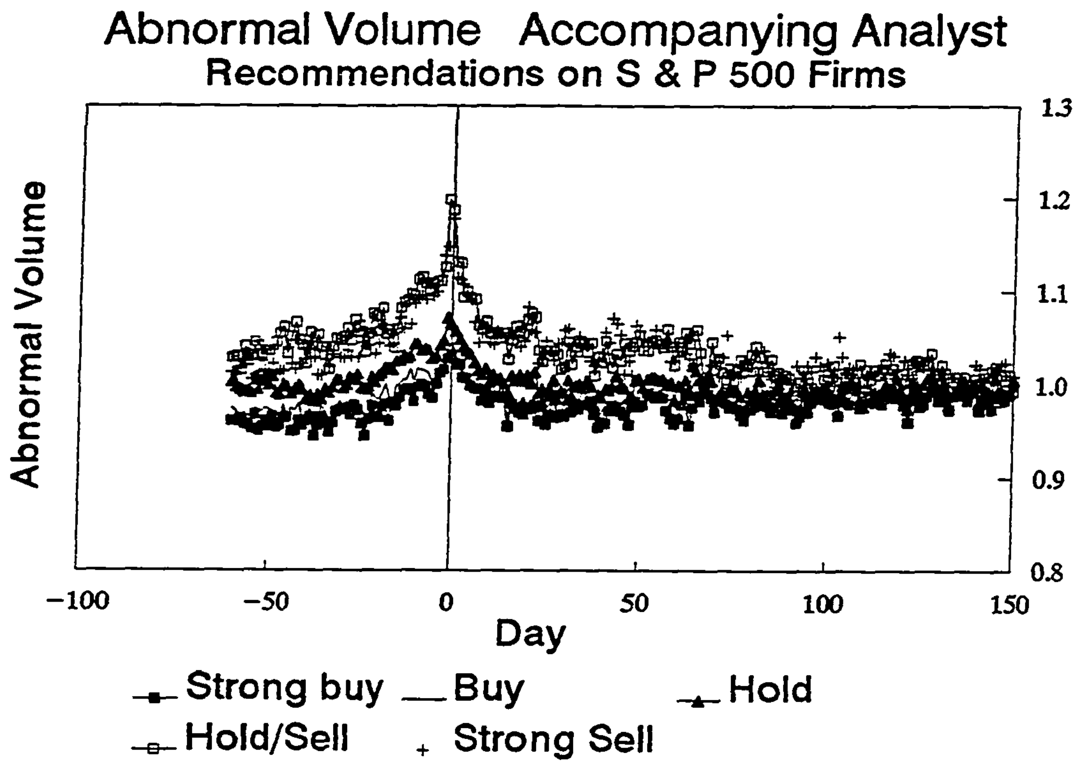
Abnormal Volume Accompanying Analyst
Recommendations on S & P 500 Firms
Abnormal Volume
1.3
1.2
1.1
1.0
0.9
0.8
−100
−50
0
50
100
150
Day
Strong buy
Buy
Hold
Hold/Sell
Strong Sell

Figure 4

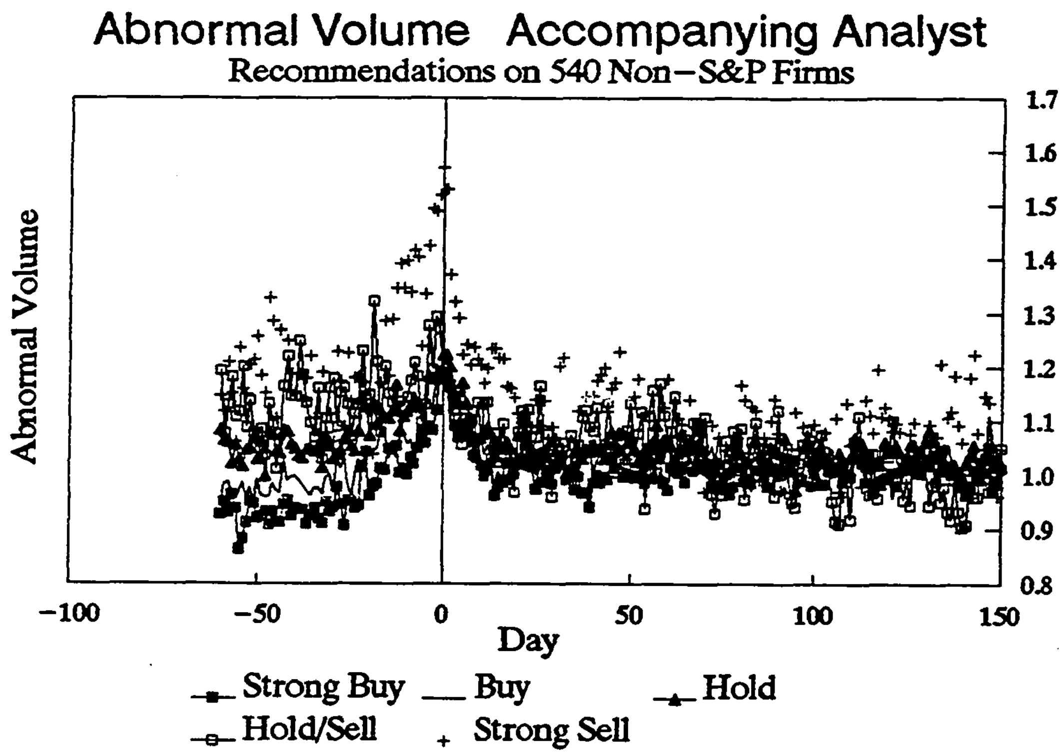
Abnormal Volume Accompanying Analyst
Recommendations on 540 Non-S&P Firms
Abnormal Volume
1.7
1.6
1.5
1.4
1.3
1.2
1.1
1.0
0.9
0.8
-100
-50
0
50
100
150
Day
Strong Buy
Buy
Hold
Hold/Sell
Strong Sell

Figure 5

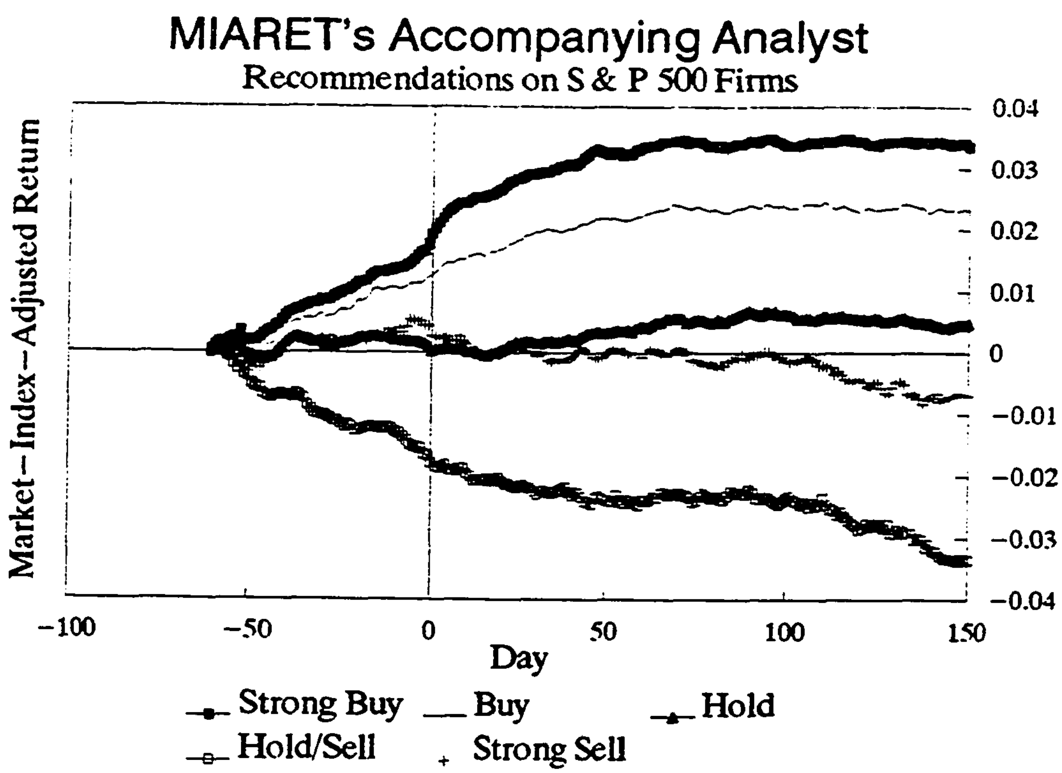
MIARET's Accompanying Analyst
Recommendations on S & P 500 Firms
Market−Index−Adjusted Return
0.04
0.03
0.02
0.01
0
−0.01
−0.02
−0.03
−0.04
−100
−50
0
50
100
150
Day
Strong Buy
Buy
Hold
Hold/Sell
Strong Sell

Figure 6

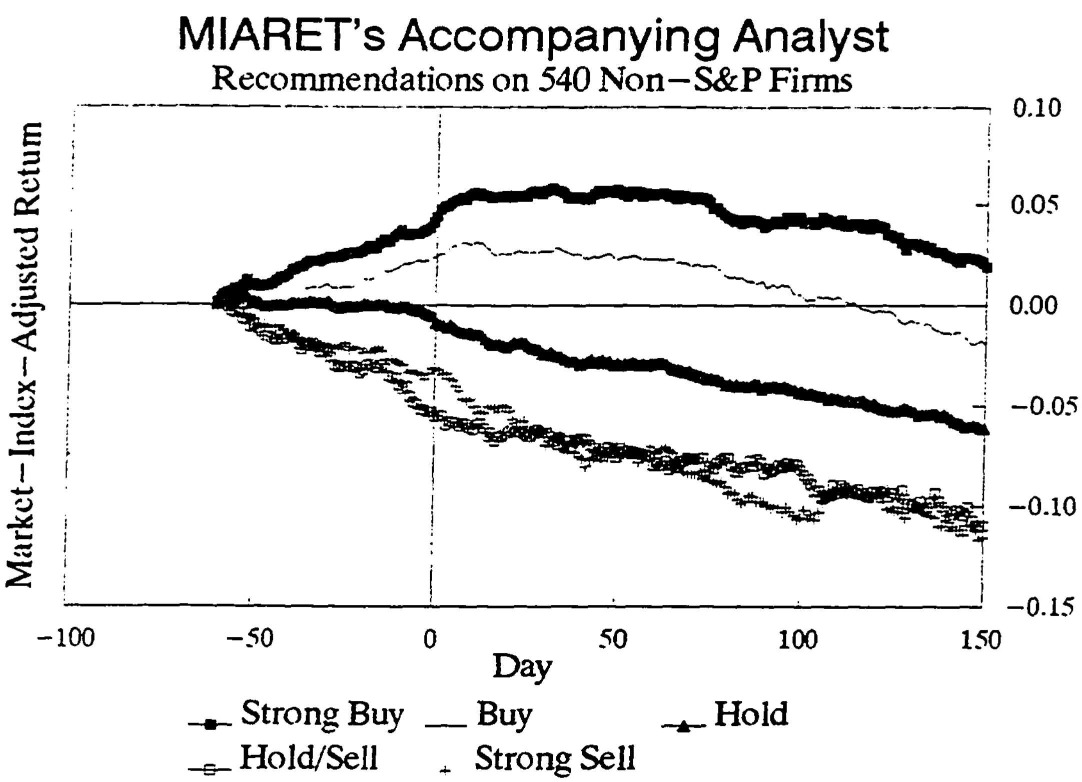
MIARET's Accompanying Analyst
Recommendations on 540 Non–S&P Firms
Market–Index–Adjusted Return
0.10
0.05
0.00
−0.05
−0.10
−0.15
−100
−50
0
50
100
150
Day
Strong Buy
Buy
Hold
Hold/Sell
Strong Sell

Figure 7

Raw Returns Accompanying Analyst Recommendations on S & P 500 Firms

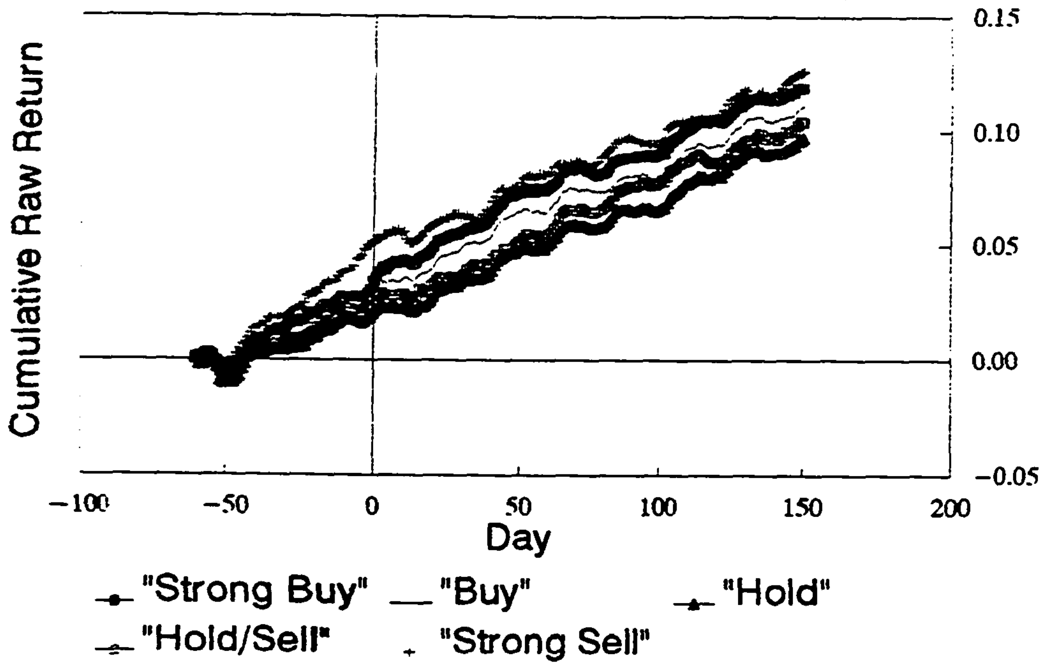

Figure 8

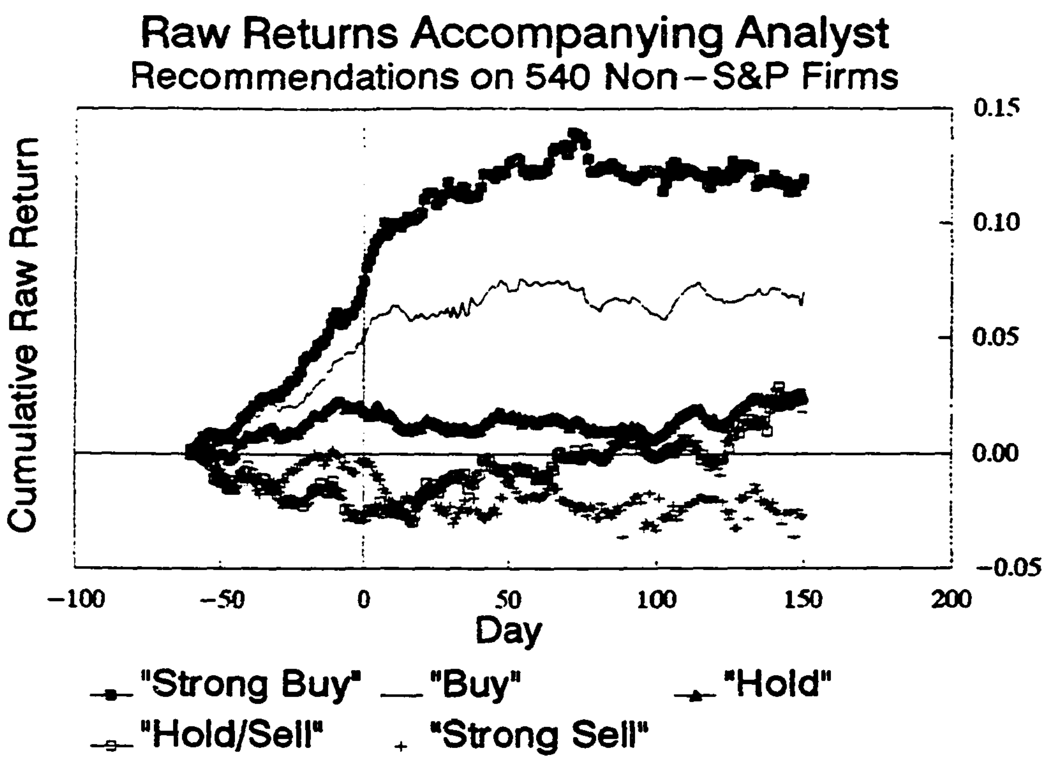
Raw Returns Accompanying Analyst
Recommendations on 540 Non-S&P Firms
Cumulative Raw Return
0.15
0.10
0.05
0.00
-0.05
-100
-50
0
50
100
150
200
Day
"Strong Buy"
"Buy"
"Hold"
"Hold/Sell"
"Strong Sell"

Table 1
Distribution of Analysts' Investment Recommendations, Fy1 Forecasts, and Fy2 Forecasts per Company (1991-1992)

Panel A: Frequency of Analysts' Investment Recommendations

Number of Recommendations per Analyst-Company Combination	Number of Combinations in 1991	Number of Combinations in 1992
Standard and Poor's 500 Firms		
1	3870	3356
2	1659	1435
3	654	555
4	263	221
5	112	86
6 or More	115	84
Total	6673	5737
540 Non-S & P Firms		
1	1157	998
2	559	553
3	254	290
4	128	133
5	68	66
6 or More	65	49
Total	2231	2089

This table provides descriptive evidence on frequency with which security analysts issue investment recommendations, current-year earnings forecasts (Fy1), and subsequent-year earnings forecasts (Fy2). Data on 1991-1992 analysts' earnings forecasts and recommendations are provided by Research Holdings Limited database.

Table 1(continued)

Panel B: Frequency of Analysts' Current-Year Earnings Forecasts

Number of Fy1 Forecasts per Analyst-Company Combination	Number of Combinations in 1991	Number of Combinations in 1992
Standard and Poor's 500 Firms		
1	1705	4759
2	1781	1685
3	1384	1320
4	903	1209
5	533	1219
6 or More	559	5300
Total	6865	15492
540 Non-S & P Firms		
1	669	1326
2	629	409
3	509	254
4	302	188
5	176	192
6 or More	176	1392
Total	2461	3761

Table 1(continued)

Panel C: Frequency of Analysts' Subsequent-Year Earnings Forecasts

Number of Fy2 Forecasts per Analyst-Company Combination	Number of Combinations in 1991	Number of Combinations in 1992
Standard and Poor's 500 Firms		
1	1478	997
2	352	414
3	188	186
4	113	131
5	54	51
6 or More	65	55
Total	2250	1834
540 Non-S & P Firms		
1	560	413
2	217	251
3	114	157
4	94	76
5	42	55
6 or More	55	87
Total	1237	1039

Table 2
Distribution of Analyst Recommendation by Ranking Level and Type of Information Intermediary

Panel A: The Number of Analyst Recommendations According to Ranking Level and Type of Information Intermediary (Percent of Total in Parentheses)

Column	STRONG BUY	BUY	HOLD	HOLD/SELL	STRONG SELL	Totals
Standard and Poor's 500 Firms						
National	6149	7609	13043	2274	841	29916
	(20.6%)	(25.4%)	(43.6%)	(7.6%)	(2.8%)	(100.0%)
Regional	8859	6190	10831	1660	1782	29322
	(30.2%)	(21.1%)	(36.9%)	(5.7%)	(6.1%)	(100.0%)
Non-Brokerage	1523	2215	3909	809	428	8884
	(17.1%)	(24.9%)	(44.0%)	(9.1%)	(4.8%)	(100.0%)
Overall	16531	16014	27783	4743	3051	68122
	(24.3%)	(23.5%)	(40.8%)	(7.0%)	(4.5%)	(100.0%)
540 Non-S & P Firms						
National	756	920	1475	199	68	3418
	(22.1%)	(26.9%)	(43.2%)	(5.8%)	(2.0%)	(100.0%)
Regional	2343	1876	2532	277	248	7276
	(32.2%)	(25.8%)	(34.8%)	(3.8%)	(3.4%)	(100.0%)
Non-Brokerage	282	329	636	133	44	1424
	(19.8%)	(23.1%)	(44.7%)	(9.3%)	(3.1%)	(100.0%)
Overall	3381	3125	4643	609	360	12118
	(27.9%)	(25.8%)	(38.3%)	(5.0%)	(3.0%)	(100.0%)

Table 2(continued)

Panel B: Difference in Percentage of Strong Buy Recommendations between National Brokerage-Firm Analysts and Regional Brokerage-Firm Analysts

Column	*STRONG BUY*		ALL Other Levels		Totals
Standard and Poor's 500 Firms					
National	6149	(7579.2)	23767	(22336.8)	29916
Regional	8859	(7428.8)	20463	(21893.3)	29322
Totals	15008		44230		59238

Contingency Test Statistic $\chi^2 = \Sigma_i \Sigma_j (O_{ij} - E_{ij})^2 / E_{ij} = 730.3$

Column	*STRONG BUY*		ALL Other Levels		Totals
540 Non-S & P Firms					
National	756	(990.5)	2662	(2427.5)	3418
Regional	2343	(2108.5)	4933	(5167.5)	7276
Totals	3099		7595		10694

Contingency Test Statistic $\chi^2 = \Sigma_i \Sigma_j (O_{ij} - E_{ij})^2 / E_{ij} = 114.9$

Panel C: Difference in percentage of Hold/Sell and Strong Sell Recommendations between Brokerage Analysts and Non-Brokerage Analysts

Column	*HOLD/SELL &STRONG SELL*		ALL Other Levels		Totals
Standard and Poor's 500 Firms					
Brokerage	6557	(6777.6)	52681	(52460.4)	59238
Non-Brokerage	1237	(1016.4)	7647	(7867.6)	8884
Totals	7794		60328		68122

Contingency Test Statistic $\chi^2 = \Sigma_i \Sigma_j (O_{ij} - E_{ij})^2 / E_{ij} = 62.1$

Column	*HOLD/SELL &STRONG SELL*		ALL Other Levels		Totals
540 Non-S & P Firms					
Brokerage	792	(855.1)	9902	(9838.9)	10694
Non-Brokerage	177	(113.9)	1247	(1310.1)	1424
Totals	969		11149		12118

Contingency Test Statistic $\chi^2 = \Sigma_i \Sigma_j (O_{ij} - E_{ij})^2 / E_{ij} = 43.1$

For Panels B and C, denote by O_{ij} the number of observations in the cell which is in the ith row and jth column. Denote by E_{ij} the estimated expected number of observations in cell i x j. Under the null hypothesis, $E_{ij} = R_i C_j / n$, where R_i and C_j are the corresponding row and column totals; n is the total number of observations. A test of association in contingency table with significance level α is based on the following decision rule:

Reject Ho if $\chi^2 = \Sigma_i \Sigma_j (O_{ij} - E_{ij})^2 / E_{ij} > \chi^2_{(2-1)(2-1),\alpha}$. Note that all χ^2 test results shown in Panels C and D are statistically significant at $\alpha = 0.001$ level.

Table 3
Market-Model-Beta-Adjusted Returns Accompanying Five Analyst Recommendation Rankings

Panel A: Abnormal Returns Accompanying the Full Sample of Investment Recommendations

	S & P 500 Firms					540 Non-S&P Firms				
Event		AR_s		$CAR_{[-2,s]}$			AR_s		$CAR_{[-2,s]}$	
Day s	N	Mean	T	Mean	T	N	Mean	T	Mean	T
Abnormal Returns Accompanying "Strong Buy" Recommendations										
-2	13,888	-.0000	-0.0	-.0000	-0.0	2,402	.0004	0.6	.0004	0.6
-1	13,888	.0007	4.1	.0007	3.0	2,402	.0024	3.2	.0027	2.8
0	13,888	.0012	7.4	.0019	6.8	2,402	.0034	4.7	.0061	5.3
1	13,888	.0007	4.6	.0025	8.3	2,402	.0035	5.3	.0097	7.1
2	13,889	.0006	4.0	.0031	9.3	2,402	.0011	1.8	.0108	7.3
3	13,889	.0006	3.9	.0037	10.2	2,402	.0015	2.4	.0123	7.6
Abnormal Returns Accompanying "Buy" Recommendations										
-2	13,161	.0000	0.3	.0000	0.3	2,301	.0001	0.2	.0001	0.2
-1	13,161	.0003	2.0	.0004	1.7	2,302	.0009	1.4	.0010	1.1
0	13,161	-.0002	-1.4	.0002	0.6	2,302	.0014	2.0	.0022	2.1
1	13,161	.0002	1.5	.0004	1.2	2,302	.0005	0.9	.0027	2.3
2	13,162	.0003	2.0	.0007	2.0	2,303	.0007	1.2	.0033	2.5
3	13,163	.0000	0.3	.0007	2.0	2,303	.0011	1.9	.0045	3.1
Abnormal Returns Accompanying "Hold" Recommendations										
-2	22,461	-.0004	-3.3	-.0004	-3.3	3,376	-.0011	-2.0	-.0011	-2.0
-1	22,461	-.0008	-5.5	-.0012	-6.1	3,376	-.0017	-2.9	-.0028	-3.4
0	22,461	-.0010	-7.2	-.0022	-9.1	3,376	-.0029	-4.8	-.0057	-5.6
1	22,461	-.0002	-1.3	-.0023	-8.7	3,376	-.0016	-2.9	-.0073	-6.4
2	22,461	-.0001	-0.8	-.0024	-8.4	3,377	-.0007	-1.4	-.0080	-6.4
3	22,463	-.0002	-1.5	-.0026	-8.3	3,377	-.0006	-1.2	-.0086	-6.4
Abnormal Returns Accompanying "Hold/Sell" Recommendations										
-2	3,926	-.0014	-3.7	-.0014	-3.7	434	.0000	0.0	.0000	0.0
-1	3,926	-.0005	-1.2	-.0019	-3.4	434	-.0035	-1.8	-.0035	-1.4
0	3,926	-.0012	-3.1	-.0031	-4.6	434	-.0029	-1.7	-.0065	-2.2
1	3,926	-.0010	-3.1	-.0041	-5.5	434	.0004	0.3	-.0060	-1.9
2	3,926	-.0006	-1.9	-.0048	-5.9	434	-.0002	-0.2	-.0063	-1.8
3	3,926	-.0003	-1.0	-.0051	-5.7	434	-.0020	-1.4	-.0083	-2.2
Abnormal Returns Accompanying "Strong Sell" Recommendations										
-2	2,650	-.0009	-1.9	-.0009	-1.9	292	.0013	0.5	.0013	0.5
-1	2,650	-.0005	-1.1	-.0014	-2.1	292	.0022	0.9	.0035	1.0
0	2,650	-.0023	-4.4	-.0037	-4.2	292	-.0024	-1.0	.0011	0.2
1	2,650	-.0007	-1.6	-.0044	-4.5	292	-.0015	-0.7	-.0004	-0.1
2	2,650	-.0009	-2.3	-.0053	-5.0	292	-.0007	-0.5	-.0012	-0.2
3	2,650	-.0006	-1.4	-.0059	-5.2	292	-.0009	-0.4	-.0020	-0.4

Table 3(continued)

Panels A, B, C and D of this table present the differential security price reactions accompanying the five levels of analyst recommendations. The sample includes all July 1987 to July 1993 investment recommendations provided for the companies by 272 major brokerage firms and research institutions. Observations are also partitioned by type of research institutions (national brokerage firm, regional brokerage firm, or non-brokerage institution). *N* denotes the number of observations. *CAR* within window *[a, b]* (AR_S) denotes the cumulative market-model-beta-adjusted returns during event period *[a, b]* (market-model-beta-adjusted returns at event date *s*), where day 0 is the analyst recommendation date. Benchmark period for estimating market-model beta: [-500,-250] U [+215, +339].

Table 3(continued)

Panel B: Abnormal Returns Accompanying National Brokerage Firm Analyst Recommendations

	S & P 500 Firms					540 Non-S&P Firms				
Event Day s	N	AR_s Mean	AR_s T	$CAR_{[-2,s]}$ Mean	$CAR_{[-2,s]}$ T	N	AR_s Mean	AR_s T	$CAR_{[-2,s]}$ Mean	$CAR_{[-2,s]}$ T
Abnormal Returns Accompanying "Strong Buy" Recommendations										
-2	5,067	.0001	0.4	.0001	0.4	552	.0009	0.7	.0009	0.7
-1	5,067	.0014	4.8	.0015	3.9	552	.0024	1.7	.0033	1.7
0	5,067	.0025	8.8	.0040	8.5	552	.0050	3.3	.0083	3.5
1	5,067	.0005	2.0	.0045	8.4	552	.0035	2.7	.0117	4.3
2	5,067	.0009	3.8	.0055	9.3	552	.0006	0.5	.0123	4.1
3	5,067	.0002	0.9	.0057	9.1	552	.0019	1.5	.0142	4.3
Abnormal Returns Accompanying "Buy" Recommendations										
-2	6,196	.0000	0.0	.0000	0.0	675	.0012	1.2	.0012	1.2
-1	6,196	.0004	1.6	.0004	1.2	675	.0010	0.9	.0022	1.5
0	6,196	-.0003	-1.0	.0001	0.3	675	.0009	0.8	.0031	1.7
1	6,196	.0005	1.9	.0006	1.3	675	.0006	0.6	.0037	1.9
2	6,196	.0002	1.0	.0008	1.6	675	-.0002	-0.2	.0035	1.6
3	6,197	.0001	0.5	.0009	1.6	675	.0022	2.3	.0057	2.4
Abnormal Returns Accompanying "Hold" Recommendations										
-2	10,528	-.0004	-1.9	-.0004	-1.9	1,093	-.0016	-1.6	-.0016	-1.6
-1	10,528	-.0013	-6.1	-.0016	-5.7	1,093	-.0017	-1.7	-.0032	-2.3
0	10,528	-.0015	-7.2	-.0032	-8.9	1,093	-.0028	-2.8	-.0060	-3.4
1	10,528	-.0003	-1.5	-.0035	-8.6	1,093	-.0011	-1.2	-.0071	-3.6
2	10,528	-.0002	-0.9	-.0036	-8.3	1,093	.0011	1.2	-.0060	-2.7
3	10,529	-.0003	-1.9	-.0039	-8.4	1,093	-.0010	-1.2	-.0069	-3.0
Abnormal Returns Accompanying "Hold/Sell" Recommendations										
-2	1,895	-.0005	-0.9	-.0005	-0.9	143	-.0019	-0.7	-.0019	-0.7
-1	1,895	.0005	0.9	.0000	0.0	143	-.0022	-0.6	-.0041	-1.0
0	1,895	-.0006	-1.1	-.0006	-0.6	143	-.0039	-1.2	-.0081	-1.5
1	1,895	-.0006	-1.3	-.0012	-1.1	143	-.0018	-0.8	-.0099	-1.8
2	1,895	-.0007	-1.5	-.0019	-1.6	143	-.0030	-1.3	-.0129	-2.2
3	1,895	-.0007	-1.4	-.0026	-2.0	143	-.0021	-0.9	-.0150	-2.6
Abnormal Returns Accompanying "Strong Sell" Recommendations										
-2	734	-.0019	-1.9	-.0019	-1.9	58	.0064	1.5	.0064	1.5
-1	734	-.0015	-1.5	-.0035	-2.3	58	-.0103	-1.4	-.0039	-0.4
0	734	-.0062	-5.1	-.0097	-4.6	58	-.0023	-0.3	-.0062	-0.5
1	734	-.0014	-1.8	-.0111	-4.9	58	.0046	0.9	-.0016	-0.1
2	734	-.0010	-1.2	-.0121	-5.0	58	.0025	0.7	.0009	0.1
3	734	-.0011	-1.5	-.0132	-5.1	52	.0103	1.7	.0112	0.8

Table 3(continued)

Panel C: Abnormal Returns Accompanying Regional Brokerage Firm Analyst Recommendations

	S & P 500 Firms					540 Non-S&P Firms				
Event Day s	N	AR_s Mean	AR_s T	$CAR_{[-2,s]}$ Mean	$CAR_{[-2,s]}$ T	N	AR_s Mean	AR_s T	$CAR_{[-2,s]}$ Mean	$CAR_{[-2,s]}$ T
Abnormal Returns Accompanying "Strong Buy" Recommendations										
-2	7,538	.0000	0.0	.0000	0.0	1,647	.0001	0.1	.0001	0.1
-1	7,538	.0003	1.6	.0003	1.1	1,647	.0024	2.5	.0024	2.0
0	7,538	.0005	2.4	.0009	2.4	1,647	.0032	3.6	.0056	3.9
1	7,538	.0009	4.2	.0017	4.2	1,647	.0038	4.5	.0094	5.6
2	7,539	.0005	2.6	.0023	5.0	1,647	.0014	1.8	.0107	5.9
3	7,539	.0008	4.2	.0031	6.4	1,647	.0016	2.2	.0123	6.3
Abnormal Returns Accompanying "Buy" Recommendations										
-2	5,259	.0002	0.7	.0002	0.7	1,431	-.0005	-0.6	-.0005	-0.6
-1	5,259	.0002	0.8	.0004	1.0	1,432	.0005	0.5	-.0000	-0.1
0	5,259	.0000	0.1	.0004	0.9	1,432	.0016	1.7	.0013	0.9
1	5,259	.0003	1.3	.0008	1.4	1,432	.0008	0.9	.0020	1.2
2	5,260	.0004	1.8	.0012	2.1	1,433	.0012	1.4	.0030	1.7
3	5,260	.0002	0.6	.0014	2.2	1,433	.0012	1.4	.0043	2.2
Abnormal Returns Accompanying "Hold" Recommendations										
-2	9,023	-.0004	-1.8	-.0004	-1.8	1,909	-.0008	-1.0	-.0008	-1.0
-1	9,023	-.0005	-2.3	-.0009	-2.9	1,909	-.0016	-2.0	-.0024	-2.1
0	9,023	-.0007	-3.2	-.0015	-4.1	1,909	-.0041	-4.8	-.0065	-4.6
1	9,023	-.0002	-1.3	-.0018	-4.3	1,909	-.0023	-3.0	-.0087	-5.5
2	9,023	.0001	0.3	-.0017	-3.8	1,910	-.0022	-2.9	-.0109	-6.3
3	9,024	-.0000	-0.4	-.0018	-3.6	1,910	-.0005	-0.7	-.0113	-6.2
Abnormal Returns Accompanying "Hold/Sell" Recommendations										
-2	1,412	-.0022	-3.7	-.0022	-3.7	214	-.0021	-1.1	-.0021	-1.1
-1	1,412	-.0012	-1.8	-.0034	-3.8	214	-.0047	-1.7	-.0067	-2.0
0	1,412	-.0026	-3.9	-.0060	-5.2	214	-.0021	-0.8	-.0088	-2.2
1	1,412	-.0019	-3.1	-.0079	-6.1	214	.0008	0.3	-.0080	-1.7
2	1,412	-.0003	-0.6	-.0082	-5.9	214	-.0005	-0.3	-.0085	-1.7
3	1,412	.0003	0.6	-.0078	-5.3	214	-.0029	-1.2	-.0114	-2.0
Abnormal Returns Accompanying "Strong Sell" Recommendations										
-2	1,560	-.0004	-0.6	-.0004	-0.6	198	-.0012	-0.4	-.0012	-0.4
-1	1,560	-.0002	-0.3	-.0006	-0.7	198	.0057	2.2	.0045	1.0
0	1,560	-.0007	-1.2	-.0013	-1.3	198	-.0014	-0.6	.0031	0.6
1	1,560	-.0006	-1.1	-.0019	-1.7	198	-.0035	-1.3	-.0005	-0.1
2	1,560	-.0009	-1.9	-.0029	-2.2	198	-.0032	-1.8	-.0037	-0.6
3	1,560	-.0006	-1.2	-.0035	-2.6	198	-.0052	-2.9	-.0089	-1.4

Table 3(continued)

Panel D: Abnormal Returns Accompanying Non-Brokerage Analyst Recommendations

	S & P 500 Firms					540 Non-S&P Firms				
Event		AR_s		$CAR_{[-2,s]}$			AR_s		$CAR_{[-2,s]}$	
Day s	N	Mean	T	Mean	T	N	Mean	T	Mean	T
Abnormal Returns Accompanying "Strong Buy" Recommendations										
-2	1,283	-.0005	-1.1	-.0005	-1.1	203	.0015	0.9	.0015	0.9
-1	1,283	-.0000	-0.1	-.0006	-0.8	203	.0023	1.1	.0038	1.4
0	1,283	-.0002	-0.4	-.0008	-0.9	203	.0008	0.4	.0046	1.3
1	1,283	.0005	1.0	-.0003	-0.4	203	.0018	1.0	.0064	1.6
2	1,283	-.0004	-0.9	-.0008	-0.7	203	.0009	0.4	.0072	1.5
3	1,283	.0004	0.8	-.0004	-0.3	203	-.0009	-0.4	.0064	1.2
Abnormal Returns Accompanying "Buy" Recommendations										
-2	1,706	-.0002	-0.4	-.0002	-0.4	195	.0010	0.5	.0010	0.5
-1	1,706	.0005	1.2	.0003	0.6	195	.0038	1.9	.0048	1.6
0	1,706	-.0009	-2.3	-.0006	-0.9	195	.0015	0.8	.0063	1.7
1	1,706	-.0008	-2.0	-.0014	-1.8	195	-.0015	-0.8	.0048	1.2
2	1,706	.0002	0.4	-.0012	-1.4	195	.0004	0.2	.0052	1.2
3	1,706	-.0005	-1.3	-.0017	-1.8	195	-.0029	-1.7	.0022	0.5
Abnormal Returns Accompanying "Hold" Recommendations										
-2	2,910	-.0008	-2.3	-.0008	-2.3	374	-.0014	-0.9	-.0014	-0.9
-1	2,910	.0003	0.7	-.0006	-1.0	374	-.0020	-1.5	-.0034	-1.7
0	2,910	.0000	0.1	-.0005	-0.9	374	.0025	1.3	-.0010	-0.4
1	2,910	.0005	1.2	-.0000	-0.1	374	.0005	0.3	-.0005	-0.2
2	2,910	-.0004	-1.1	-.0005	-0.6	374	.0011	0.8	.0006	0.2
3	2,910	.0000	0.1	-.0004	-0.5	374	-.0000	-0.0	.0005	0.2
Abnormal Returns Accompanying "Hold/Sell" Recommendations										
-2	619	-.0024	-2.5	-.0024	-2.5	77	.0094	2.4	.0094	2.4
-1	619	-.0018	-2.1	-.0042	-3.5	77	-.0029	-0.7	.0065	0.9
0	619	.0001	0.1	-.0041	-2.6	77	-.0035	-1.3	.0030	0.4
1	619	-.0006	-0.7	-.0047	-2.4	77	.0035	1.1	.0065	0.9
2	619	-.0010	-1.2	-.0058	-2.9	77	.0057	1.8	.0122	1.4
3	619	-.0008	-0.9	-.0066	-2.9	77	.0005	0.2	.0127	1.5
Abnormal Returns Accompanying "Strong Sell" Recommendations										
-2	356	-.0011	-0.9	-.0011	-0.9	36	.0070	0.9	.0070	0.9
-1	356	.0002	0.2	-.0009	-0.5	36	.0031	0.5	.0102	1.3
0	356	-.0010	-0.8	-.0019	-0.9	36	-.0079	-1.4	.0022	0.2
1	356	.0005	0.5	-.0013	-0.6	36	-.0004	-0.1	.0018	0.2
2	356	-.0007	-0.6	-.0020	-0.8	36	.0074	1.4	.0092	0.8
3	356	.0004	0.3	-.0016	-0.6	36	.0052	0.8	.0145	1.0

Table 3(continued)

Panel E: Results of Specification Check of Whether Herding Effects Result in Significant Abnormal Returns, with Each Observation Representing Mean [-1,1] Beta-Adjusted Returns for Each Six-Trading-Day Period

	S & P 500 Firms				540 Non-S&P Firms			
	N	Mean	Median	T	N	Mean	Median	T
Abnormal [-1,1] Returns Accompanying Analyst Recommendations (Overall Sample)								
$CAR_{STRONG\ BUY}$	207	.0042	.0034	5.00	199	.0098	.0036	4.49
CAR_{BUY}	201	.0008	-.0004	0.85	194	.0038	.0025	2.00
CAR_{HOLD}	201	-.0037	-.0033	-5.29	195	-.0093	-.0083	-4.85
$CAR_{HOLD/SELL}$	187	-.0091	-.0060	-4.45	113	-.0126	-.0111	-2.47
$CAR_{STRONG\ SELL}$	186	-.0039	-.0025	-2.47	110	-.0153	-.0059	-2.14
Abnormal [-1,1] Returns Accompanying National Brokerage Analyst Recommendations								
$CAR_{STRONG\ BUY}$	189	.0076	.0058	6.26	143	.0121	.0031	2.92
CAR_{BUY}	188	-.0007	-.0012	-0.56	130	.0037	.0050	1.23
CAR_{HOLD}	190	-.0066	-.0046	-6.19	149	-.0177	-.0072	-5.20
$CAR_{HOLD/SELL}$	145	-.0181	-.0085	-4.95	56	-.0125	-.0061	-1.78
$CAR_{STRONG\ SELL}$	126	-.0059	-.0048	-1.30	37	-.0362	-.0075	-2.49
Abnormal [-1,1] Returns Accompanying Regional Brokerage Analyst Recommendations								
$CAR_{STRONG\ BUY}$	206	.0033	.0021	3.45	193	.0091	.0025	3.43
CAR_{BUY}	197	.0008	.0001	0.66	183	.0023	.0024	0.85
CAR_{HOLD}	198	-.0034	-.0025	-3.27	191	-.0102	-.0064	-3.88
$CAR_{HOLD/SELL}$	168	-.0075	-.0058	-3.37	79	-.0202	-.0132	-2.80
$CAR_{STRONG\ SELL}$	164	-.0025	-.0013	-1.19	87	-.0094	-.0064	-1.54
Abnormal [-1,1] Returns Accompanying Non-Brokerage Analyst Recommendations								
$CAR_{STRONG\ BUY}$	161	.0011	.0004	0.58	77	.0021	.0009	0.48
CAR_{BUY}	101	-.0028	-.0029	-1.79	67	.0012	-.0047	0.21
CAR_{HOLD}	156	-.0010	-.0016	-0.66	79	-.0041	-.0061	-1.04
$CAR_{HOLD/SELL}$	82	-.0005	-.0019	-0.18	39	-.0059	-.0099	-0.94
$CAR_{STRONG\ SELL}$	84	-.0052	-.0012	-1.58	19	-.0028	-.0147	-0.20

Panel E of Table 3 presents the results of my specification checks examining *mean* [-1,1] market-model-beta adjusted returns for recommendations issued on the second, thc third, the fourth, and the fifth trading days of each six-trading-day period. I partition my observations into 207 distinct six-trading-day periods and exclude recommendations issued on both the first and the last trading days of each period. Thus there exists no over-lapping in event window for abnormal returns; all observations are independently distributed. The results are consistent with the findings reported in Panels A, B, C, and D of Table 3, suggesting that the herding potential of analysts' issuing investment recommendations is not sufficient to negate the statistical relevance of either the ranking or the type variable.

Results of tests examining mean [-1,0] abnormal returns for recommendations issued on the second, the third, and the fourth trading days of each four-trading-day period are also consistent with the findings reported in Panels A, B, C, and D of Table 3 and are available upon request.

Table 3(continued)

Panel F: Abnormal Returns Accompanying Analyst Recommendations Issued within [-2,1] surrounding Quarterly Earnings Announcement Dates

	S & P 500 Firms				540 Non-S&P Firms			
	N	Mean	Median	T	N	Mean	Median	T
Abnormal [-2,3] Returns Accompanying Analyst Recommendations (Overall Sample)								
$CAR_{STRONG\ BUY}$	781	.0127	.0083	6.53	152	.0353	.0191	4.18
CAR_{BUY}	714	.0048	.0019	2.00	140	.0101	.0031	1.48
CAR_{HOLD}	1,235	-.0075	-.0051	-4.02	195	-.0293	-.0172	-4.37
$CAR_{HOLD/SELL}$	202	-.0151	-.0133	-2.86	17	-.0618	-.0405	-2.21
$CAR_{STRONG\ SELL}$	152	-.0269	-.0138	-4.30	18	-.0527	-.0331	-1.97
Abnormal [-2,3] Returns Accompanying National Brokerage Analyst Recommendations								
$CAR_{STRONG\ BUY}$	339	.0160	.0108	5.10	43	.0407	.0170	2.98
CAR_{BUY}	330	.0049	.0029	1.26	37	.0252	.0144	2.31
CAR_{HOLD}	635	-.0079	-.0055	-2.97	53	-.0453	-.0192	-3.26
$CAR_{HOLD/SELL}$	88	-.0239	-.0198	-2.81	7	-.0514	-.0405	-1.03
$CAR_{STRONG\ SELL}$	53	-.0494	-.0310	-3.90	5	-.0256	-.0131	-0.40
Abnormal [-2,3] Returns Accompanying Regional Brokerage Analyst Recommendations								
$CAR_{STRONG\ BUY}$	380	.0128	.0085	4.65	101	.0320	.0242	2.88
CAR_{BUY}	325	.0040	-.0003	1.23	94	.0043	-.0027	0.49
CAR_{HOLD}	481	-.0100	-.0058	-3.37	129	-.0258	-.0145	-3.31
$CAR_{HOLD/SELL}$	91	-.0132	-.0125	-1.89	7	-.0811	-.0370	-1.67
$CAR_{STRONG\ SELL}$	73	-.0129	-.0113	-1.60	9	-.0791	-.0404	-2.20
Abnormal [-2,3] Returns Accompanying Non-Brokerage Analyst Recommendations								
$CAR_{STRONG\ BUY}$	62	-.0058	-.0040	-1.40	8	.0492	.0500	1.53
CAR_{BUY}	59	.0089	.0021	1.16	9	.0086	-.0143	0.32
CAR_{HOLD}	119	.0043	.0020	0.76	13	.0017	-.0085	0.06
$CAR_{HOLD/SELL}$	23	.0112	.0002	0.64	3	-.0413	-.0458	-1.37
$CAR_{STRONG\ SELL}$	26	-.0204	-.0116	-1.91	4	-.0269	-.0325	-0.53

Panels F and G of Table 3 present the results of my specification checks of whether analyst recommendations coincide with earnings announcements are the only recommendations that are informative. I partition my observations by whether their recommendation dates are within a four-day period surrounding quarterly earnings announcements. Specifically, Panel F (Panel G) reports test statistics for [-2,3] market-model-beta adjusted returns for recommendations issued within (outside) the [-2,1] earnings announcement period. Moreover, for significance tests reported in Panel G, I exclude all the observations that do not have quarterly earnings announcement dates available in COMPUSTAT from the samples.

Table 3(continued)

Panel G: Abnormal Returns Accompanying Analyst Recommendations Issued outside the [-2,1] Period surrounding Quarterly Earnings Announcement Dates

	S & P 500 Firms				540 Non-S&P Firms			
	N	Mean	Median	T	N	Mean	Median	T
Abnormal [-2,3] Returns Accompanying Analyst Recommendations (Overall Sample)								
$CAR_{STRONG\ BUY}$	15,279	.0040	.0019	11.33	2,812	.0131	.0066	9.12
CAR_{BUY}	14,750	.0006	-.0002	1.73	2,659	.0040	.0004	2.94
CAR_{HOLD}	25,623	-.0033	-.0028	-11.13	3,969	-.0088	-.0069	-7.12
$CAR_{HOLD/SELL}$	4,411	-.0054	-.0044	-6.42	527	-.0055	-.0041	-1.60
$CAR_{STRONG\ SELL}$	2,821	-.0060	-.0039	-5.57	298	-.0025	-.0011	-0.42
Abnormal [-2,3] Returns Accompanying National Brokerage Analyst Recommendations								
$CAR_{STRONG\ BUY}$	5,634	.0062	.0036	10.16	636	.0172	.0101	5.80
CAR_{BUY}	7,013	.0011	-.0001	2.16	787	.0033	.0008	1.40
CAR_{HOLD}	11,992	-.0050	-.0038	-11.38	1,300	-.0077	-.0038	-3.59
$CAR_{HOLD/SELL}$	2,131	-.0020	-.0012	-1.65	177	-.0113	-.0041	1.90
$CAR_{STRONG\ SELL}$	765	-.0110	-.0056	-4.58	58	.0135	.0038	0.88
Abnormal [-2,3] Returns Accompanying Regional Brokerage Analyst Recommendations								
$CAR_{STRONG\ BUY}$	8,220	.0031	.0012	6.59	1,946	.0124	.0056	7.23
CAR_{BUY}	5,661	.0007	-.0001	1.18	1,576	.0042	.0005	2.26
CAR_{HOLD}	10,004	-.0020	-.0019	-4.38	2,121	-.0115	-.0090	-6.51
$CAR_{HOLD/SELL}$	1,529	-.0090	-.0075	-6.21	235	-.0095	-.0066	-1.81
$CAR_{STRONG\ SELL}$	1,668	-.0048	-.0036	-3.64	203	-.0113	-.0038	-1.59
Abnormal [-2,3] Returns Accompanying Non-Brokerage Analyst Recommendations								
$CAR_{STRONG\ BUY}$	1,425	.0006	-.0009	0.57	230	.0069	.0019	1.32
CAR_{BUY}	2,076	-.0013	-.0009	-1.57	296	.0051	-.0018	1.32
CAR_{HOLD}	3,627	-.0011	-.0018	-1.36	548	-.0008	-.0040	-0.30
$CAR_{HOLD/SELL}$	751	-.0077	-.0056	-3.88	115	.0117	.0003	1.76
$CAR_{STRONG\ SELL}$	388	-.0013	-.0019	-0.49	37	.0207	.0063	1.64

Table 4
Abnormal Trading Volume Accompanying Five Analyst Recommendation Rankings

Panel A: Abnormal Volume on the Six Event Days Surrounding Analyst Recommendations

	Standard & Poor's 500			540 Non-S&P Firms		
Day	N	Mean AV	T_{AV-1}	N	Mean AV	T_{AV-1}
Abnormal Volume Accompanying Analyst Recommendations (Overall)						
-2	56,320	1.378	48.6	7,852	2.621	25.2
-1	56,319	1.422	49.7	7,878	2.627	22.7
0	56,320	1.452	39.5	7,858	2.723	26.0
1	56,327	1.378	43.1	7,845	2.537	29.6
2	56,331	1.363	45.9	7,843	2.480	20.1
3	56,331	1.351	38.8	7,862	2.360	23.9
Abnormal Volume Accompanying "Strong Buy" Recommendations						
-2	13,940	1.298	23.0	2,123	2.468	12.1
-1	13,941	1.335	26.1	2,133	2.655	14.3
0	13,941	1.357	19.2	2,125	2.522	15.9
1	13,944	1.308	23.3	2,118	2.379	17.3
2	13,944	1.297	25.8	2,121	2.399	15.2
3	13,944	1.272	25.3	2,117	2.431	11.5
Abnormal Volume Accompanying "Buy" Recommendations						
-2	13,220	1.368	21.0	2,047	2.759	14.4
-1	13,221	1.361	25.0	2,057	2.534	11.9
0	13,220	1.389	22.7	2,045	2.882	11.9
1	13,221	1.333	22.1	2,052	2.661	14.7
2	13,223	1.331	18.7	2,046	2.294	15.2
3	13,223	1.320	14.2	2,057	2.228	14.1
Abnormal Volume Accompanying "Hold" Recommendations						
-2	22,552	1.378	31.6	3,025	2.572	16.7
-1	22,549	1.442	29.3	3,022	2.617	11.9
0	22,551	1.478	21.3	3,030	2.713	16.0
1	22,555	1.394	27.3	3,014	2.484	17.2
2	22,557	1.375	28.9	3,014	2.673	10.0
3	22,557	1.373	25.1	3,028	2.410	14.1
Abnormal Volume Accompanying "Hold/Sell" Recommendations						
-2	3,946	1.543	16.6	389	2.881	3.7
-1	3,946	1.678	15.7	393	2.557	6.7
0	3,946	1.668	19.5	389	2.581	6.5
1	3,946	1.558	10.0	389	2.513	7.3
2	3,945	1.505	17.3	390	2.320	6.0
3	3,945	1.501	12.7	389	2.131	7.1
Abnormal Volume Accompanying "Strong Sell" Recommendations						
-2	2,662	1.604	12.8	258	2.944	6.3
-1	2,662	1.624	13.5	273	3.308	6.3
0	2,662	1.710	12.9	269	3.421	6.1
1	2,661	1.559	12.2	272	3.459	7.2
2	2,662	1.548	10.8	272	2.605	7.2
3	2,662	1.500	13.4	271	2.567	6.3

Table 4(continued)

Panel B: Average Daily Abnormal Trading Volume during Event Period [-2, 3]

Ranking Level	S & P 500 Firms N	Mean	Median	T_{AV-1}	540 Non-S&P Firms N	Mean	Median	T_{AV-1}
Overall Recommendations								
STRONG BUY	12,894	1.301	1.110	34.2	2,241	2.345	1.480	21.2
BUY	12,351	1.341	1.120	33.6	2,145	2.447	1.480	20.6
HOLD	20,996	1.400	1.140	43.6	3,139	2.482	1.530	23.0
HOLD/SELL	3,701	1.579	1.230	22.7	401	2.428	1.610	9.1
STRONG SELL	2,484	1.596	1.220	17.6	280	2.951	1.810	9.7
National Brokerage Firm Analyst Recommendations								
STRONG BUY	4,691	1.317	1.120	20.9	513	2.179	1.470	11.7
BUY	5,792	1.348	1.130	24.7	643	2.244	1.380	11.9
HOLD	9,833	1.431	1.140	29.6	1,036	2.650	1.550	11.4
HOLD/SELL	1,810	1.644	1.250	15.3	134	2.265	1.665	7.1
STRONG SELL	704	1.755	1.325	9.8	58	3.720	2.490	5.3
Regional Brokerage Firm Analyst Recommendations								
STRONG BUY	6,993	1.298	1.110	24.9	1,538	2.418	1.490	17.4
BUY	5,018	1.354	1.110	20.0	1,344	2.558	1.540	16.1
HOLD	8,536	1.375	1.120	27.4	1,800	2.447	1.530	19.9
HOLD/SELL	1,348	1.578	1.220	14.9	204	2.444	1.575	5.7
STRONG SELL	1,448	1.517	1.180	12.9	190	2.839	1.720	7.6
Non-Brokerage Analyst Recommendations								
STRONG BUY	1,210	1.259	1.070	10.8	190	2.211	1.270	5.3
BUY	1,541	1.276	1.110	12.2	158	2.327	1.315	6.0
HOLD	2,627	1.368	1.160	17.4	303	2.120	1.410	9.3
HOLD/SELL	543	1.364	1.160	9.9	63	2.722	1.660	4.2
STRONG SELL	332	1.601	1.230	7.5	32	2.224	1.915	3.8

Table 4(continued)

Panel C: Abnormal Volume Over the Fifty-One-Day Event Period Surrounding Analyst Recommendation Dates

Ranking Level	Standard & Poor's 500 N	Mean AV	T_{AV-1}	540 Non-S&P Firms N	Mean AV	T_{AV-1}
STRONG BUY	14,036	1.156	27.5	2,241	2.079	27.9
BUY	13,308	1.191	32.6	2,145	2.207	29.2
HOLD	22,672	1.242	48.8	3,139	2.233	36.5
HOLD/SELL	3,958	1.366	26.4	401	2.254	15.0
STRONG SELL	2,668	1.358	20.6	280	2.420	12.3
OVERALL	56,642	1.223	72.4	8,206	2.191	57.6

This table presents statistics of abnormal trading volume over short event windows (Panels A and B) and long event windows (Panel C) surrounding analyst recommendations for each of the five levels of recommendations. The sample includes all July 1987 to July 1993 investment recommendations provided for the companies by 272 major brokerage firms and research institutions.

AV denotes the abnormal trading volume measure. It is calculated by applying the approach introduced by Ajinkya and Jain (1989) and Barber and Loeffler (1993). A transformation taking natural log of one plus trading volume is performed to obtain a normally distributed explanatory variable. The market model for the log transformed trading volume

$$V_{jt} = \alpha_j + \beta_j V_{mt} + \varepsilon_{jt}$$

is then estimated using generalized least squares for security *j* from day -125 to day -26. The event window is defined as 51 trading days centered around the recommendation date. The total volume in the market, V_{mt}, is defined as aggregate S & P 500 firm trading volume (aggregate U.S. security market trading volume) for *S & P 500 firms* (*Non-S&P firms*). The exponent of the difference between the actual and the predicted log transformed volume, or *AV*, measures the ratio of (1 + actual volume) to (1+ predicted volume). For example, *AV* =2 means that actual volume is approximately double predicted volume during the event period.

T_{AV-1} denotes the t-statistics for the test with null hypothesis that *AV* is less than or equal to one and alternative hypothesis that *AV* is greater than one.

Table 5
Linear Regression Tests: Market-Model-Adjusted Security Returns Accompanying Analysts' Recommendations, Recommendation Changes, and Price-Deflated Earnings Forecast Revisions

Panel A: Linear Regression Tests of Abnormal Market Returns during Event-Period [-1,0], with Level (Change) of Investment Recommendation Being Quantified and Coded from -2 to 2 (from -4 to 4).

A-1 Model $CAR_{[-1,0]} = \beta_0 + \beta_1\ FREV + \varepsilon$

FY Year	N	ADJ.R^2	β_0	t(β_0)	β_1 FREV	t(β_1)	F-Value
Standard & Poor's 500 Firms							
1	17886	.0010	-.002	-8.6	.0229	4.4	19.547
2	773	.0030	-.001	-0.5	.1356	1.8	3.330
540 Randomly Selected Non-S&P Firms							
1	3077	.0011	-.002	-1.8	.0424	2.1	4.439
2	363	.0103	-.001	-0.5	.1403	2.2	4.758

A-2 Model $CAR_{[-1,0]} = \beta_0 + \beta_1\ Rec + \varepsilon$

FY Year	N	ADJ.R^2	β_0	t(β_0)	β_1 Rec	t(β_1)	F-Value
Standard & Poor's 500 Firms							
1	17886	.0099	-.004	-14.4	-.0032	-13.4	179.596
2	773	.0032	-.002	-1.6	-.0023	-1.9	3.517
540 Randomly Selected Non-S&P Firms							
1	3077	.0182	-.007	-6.0	-.0069	-7.6	58.167
2	363	.0276	-.007	-2.3	-.0074	-3.4	11.276

Table 5(continued)

A-3 Model $CAR_{[-1,0]} = \beta_o + \beta_1 \, Rec + \beta_2 \, ChgRec + \varepsilon$

FY Year	N	ADJ.R^2	β_o	$t(\beta_o)$	β_1 *Rec*	$t(\beta_1)$	β_2 *ChgRec*	$t(\beta_2)$	F-Value
Standard & Poor's 500 Firms									
1	17885	.0108	-.004	-14.9	-.0041	-12.8	.0010	4.1	98.204
2	773	.0020	-.003	-1.5	-.0026	-1.6	.0002	0.2	1.776
540 Randomly Selected Non-S&P Firms									
1	3068	.0181	-.007	-5.6	-.0070	-6.0	.0001	0.1	29.288
2	362	.0264	-.006	-2.0	-.0066	-2.2	-.0010	-0.4	5.894

A-4 Model $CAR_{[-1,0]} = \beta_o + \beta_1 \, Rec + \beta_2 \, ChgRec + \beta_3 \, FREV + \varepsilon$

FY Year	N	ADJ.R^2	β_o	$t(\beta_o)$	β_1 *Rec*	$t(\beta_1)$	β_2 *ChgRec*	$t(\beta_2)$	β_3 *FREV*	$t(\beta_3)$
Standard & Poor's 500 Firms										
1	17885	.0114	-.004	-14.3	-.0040	-12.6	.001	4.1	.018	3.5
2	773	.0032	-.002	-1.2	-.0021	-1.2	.000	0.2	.106	1.4
540 Randomly Selected Non-S&P Firms										
1	3068	.0185	-.006	-5.2	-.0069	-5.9	.000	0.0	.029	1.4
2	362	.0308	-.006	-1.9	-.0058	-1.9	-.001	-0.5	.105	1.6

In this table, $CAR_{[s,\,t]}$ denotes cumulative market-model-beta-adjusted returns from the beginning of day s to the end of day t, where day 0 is the recommendation date. For Panel A, *FY* denotes the fiscal year, where *FY1* (*FY2*) represents the current-year (subsequent-year) EPS forecast revision. *N* denotes the number of observations. *Rec* denotes the level of analyst investment recommendation. *REC* takes the value of -2 when analyst recommends *Strong Buy*; *REC*=-1 means *Buy*; *REC*=0 means *Hold*; *REC*=1 means *Hold/Sell*; *REC*=2 means *Sell*. *ChgRec* denotes the current analyst recommendation rating less the most recent rating. *FREV:* is defined as analysts' current earnings forecast less the most recent forecast, deflated by the closing price five trading days prior to the estimate date of the previous forecast.

For Panels B and C, vector [*L1*, *L2*, *L3*, *L4*] is set to be equal to

(1). [1, 1, 1, 1], if the security is given a *Strong Buy* recommendation,
(2). [0, 1, 1, 1], if the security is given a *Buy* recommendation,
(3). [0, 0, 1, 1], if the security is given a *Hold* recommendation,
(4). [0, 0, 0, 1], if the security is given a *Hold/Sell* recommendation, or
(5). [0, 0, 0, 0], if the security is given a *Strong Sell* recommendation,

FREV1 (*FREV2*) denotes revision of current-year (subsequent-year) earnings forecast.
Test samples for Panel B (Panel C): observations with *FREV1* (*FREV2*) and investment recommendations issued contemporaneously.

Table 5(continued)

Panel B: Abnormal Market Reaction Tests with Dummy Variables L_1, L_2, L_3, and L_4 Collectively Representing Levels of Analyst Recommendations for S & P 500 Observations with Analysts' Fy1 Forecast Revisions Available

	Event Window [s, t]			
Column	[-2,3]	[-2,2]	[-1,0]	[0,3]
B-1 Model $CAR_{[s,t]} = \beta_o + \beta_{FREV1}\, FREV1 + \varepsilon$				
N	17,889	17,889	17,889	17,890
β_o	-.0034 (-8.6)	-.0027 (-7.2)	-.0022 (-8.6)	-.0022 (-7.0)
β_{FREV1}	.0106 (1.3)	.0182 (2.4)	.0229 (4.4)	.0008 (0.1)
F-Value	1.75	5.87	19.55	0.01
ADJ.R^2	.0000	.0003	.0010	-.0001
B-2 Model $CAR_{[s,t]} = \beta_o + \Sigma_{i=1,4}\, \beta_{Li}\, Li + \varepsilon$				
N	17,889	17,889	17,889	17,890
β_o	-.0153 (-7.8)	-.0160 (-8.7)	-.0115 (-9.1)	-.0078 (-5.0)
β_{L1}	.0060 (5.2)	.0048 (4.4)	.0039 (5.2)	.0045 (4.9)
β_{L2}	.0057 (5.6)	.0058 (6.1)	.0035 (5.4)	.0033 (4.0)
β_{L3}	.0023 (1.5)	.0019 (1.3)	-.0002 (-0.2)	.0017 (1.4)
β_{L4}	.0059 (2.4)	.0080 (3.5)	.0071 (4.6)	.0015 (0.8)
F-Value	49.02	51.29	48.27	30.65
Adj-R^2	.0106	.0111	.0105	.0066
B-3 Model $CAR_{[s,t]} = \beta_o + \Sigma_{i=1,4}\, \beta_{Li}\, Li + \beta_{ChgRec}\, ChgRec + \varepsilon$				
N	17,888	17,888	17,889	17,889
β_o	-.0190 (-9.0)	-.0198 (-10.1)	-.0136 (-10.0)	-.0090 (-5.4)
β_{L1}	.0076 (6.3)	.0064 (5.7)	.0047 (6.1)	.0050 (5.3)
β_{L2}	.0073 (6.8)	.0074 (7.4)	.0044 (6.4)	.0038 (4.5)
β_{L3}	.0037 (2.4)	.0034 (2.3)	.0006 (0.6)	.0022 (1.8)
β_{L4}	.0074 (3.0)	.0095 (4.2)	.0079 (5.0)	.0020 (1.0)
β_{ChgRec}	.0018 (4.9)	.0018 (5.3)	.0010 (4.1)	.0006 (2.1)
F-Value	43.99	46.80	42.04	25.38
Adj-R^2	.0119	.0126	.0113	.0068
B-4 Model $CAR_{[s,t]} = \beta_o + \Sigma_{i=1,4}\, \beta_{Li}\, Li + \beta_{ChgRec}\, ChgRec + \beta_{FREV1}\, FREV1 + \varepsilon$				
N	17,888	17,888	17,889	17,889
β_o	-.0189 (-9.0)	-.0196 (-10.0)	-.0133 (-9.8)	-.0091 (-5.4)
β_{L1}	.0076 (6.3)	.0064 (5.7)	.0047 (6.2)	.0050 (5.3)
β_{L2}	.0073 (6.8)	.0074 (7.4)	.0043 (6.2)	.0038 (4.5)
β_{L3}	.0037 (2.4)	.0033 (2.3)	.0005 (0.4)	.0022 (1.8)
β_{L4}	.0074 (3.0)	.0095 (4.2)	.0079 (5.0)	.0020 (1.0)
β_{ChgRec}	.0018 (4.9)	.0018 (5.3)	.0010 (4.1)	.0006 (2.1)
β_{FREV1}	.0036 (0.5)	.0113 (1.5)	.0187 (3.6)	-.0034 (-0.5)
F-Value	36.69	39.39	37.25	21.20
Adj-R^2	.0118	.0127	.0120	.0067

Table 5(continued)

Panel C: Abnormal Market Reaction Tests with Dummy Variables L_1, L_2, L_3, and L_4 Collectively Representing Levels of Analyst Recommendations for S & P 500 Observations with Analysts' Fy2 Forecast Revisions Available

Column	Event Window [s, t] [-2,3]	[-2,2]	[-1,0]	[0,3]
C-1 Model $CAR_{[s,t]} = \beta_o + \beta_{FREV2} FREV2 + \varepsilon$				
N	773	773	773	773
β_o	-.0001 (-0.0)	.0010 (0.5)	-.0006 (-0.5)	.0006 (0.4)
β_{FREV2}	.0273 (2.4)	.3261 (3.0)	.1356 (1.8)	.2134 (2.6)
F-Value	5.68	9.08	3.33	6.76
Adj-R^2	.0060	.0104	.0030	.0074
C-2 Model $CAR_{[s,t]} = \beta_o + \Sigma_{i=1,4} \beta_{Li} Li + \varepsilon$				
N	773	773	773	773
β_o	-.0489 (-4.5)	-.0495 (-4.8)	-.0175 (-2.4)	-.0231 (-2.9)
β_{L1}	.0017 (0.3)	.0006 (0.1)	.0034 (0.9)	.0030 (0.8)
β_{L2}	.0109 (2.1)	.0121 (2.5)	-.0012 (-0.3)	.0066 (1.8)
β_{L3}	-.0056 (-0.6)	-.0049 (-0.6)	.0030 (0.5)	-.0068 (-1.0)
β_{L4}	.0488 (3.5)	.0495 (3.8)	.0140 (1.6)	.0261 (2.6)
F-Value	7.06	8.58	1.73	4.29
Adj-R^2	.0304	.0378	.0037	.0168
C-3 Model $CAR_{[s,t]} = \beta_o + \Sigma_{i=1,4} \beta_{Li} Li + \beta_{ChgRec} ChgRec + \varepsilon$				
N	773	773	773	773
β_o	-.0537 (-4.7)	-.0529 (-4.9)	-.0177 (-2.3)	-.0246 (-3.0)
β_{L1}	.0039 (0.7)	.0021 (0.4)	.0035 (0.9)	.0037 (0.9)
β_{L2}	.0131 (2.4)	.0137 (2.6)	-.0011 (-0.3)	.0073 (1.9)
β_{L3}	-.0041 (-0.5)	-.0039 (-0.4)	.0030 (0.5)	-.0064 (-1.0)
β_{L4}	.0506 (3.7)	.0508 (3.9)	.0141 (1.6)	.0266 (2.7)
β_{ChgRec}	.0023 (1.2)	.0016 (0.9)	.0001 (0.1)	.0007 (0.5)
F-Value	5.96	7.03	1.38	3.49
Adj-R^2	.0311	.0376	.0025	.0159
C-4 Model $CAR_{[s,t]} = \beta_o + \Sigma_{i=1,4} \beta_{Li} Li + \beta_{ChgRec} ChgRec + \beta_{FREV2} FREV2 + \varepsilon$				
N	773	773	773	773
β_o	-.0515 (-4.4)	-.0501 (-4.6)	-.0165 (-2.2)	-.0226 (-2.7)
β_{L1}	.0028 (0.5)	.0008 (0.1)	.0029 (0.8)	.0027 (0.7)
β_{L2}	.0127 (2.3)	.0132 (2.6)	-.0012 (-0.3)	.0070 (1.8)
β_{L3}	-.0071 (-0.8)	-.0077 (-0.9)	.0014 (0.2)	-.0091 (-1.4)
β_{L4}	.0520 (3.8)	.0525 (4.0)	.0149 (1.6)	.0279 (2.8)
β_{ChgRec}	.0022 (1.2)	.0015 (0.9)	.0001 (0.1)	.0007 (0.5)
β_{FREV2}	.1947 (1.6)	.2486 (2.2)	.1082 (1.4)	.1780 (2.1)
F-Value	5.43	6.72	1.47	3.64
Adj-R^2	.0333	.0426	.0037	.0201

Table 6
Long-Windowed Market-Model-Beta-Adjusted Returns Associated with Five Analyst Recommendation Rankings

Panel A: Excess Returns Test Results with One-Hundred-and-Fifty-One-Day ([0, 150]) Event Windows

	S & P 500 Firms				540 Non-S&P Firms			
	N	Mean	Median	T	N	Mean	Median	T
Overall Recommendations								
$CAR_{STRONG\ BUY}$	13,819	.008	-.0126	3.91	2,326	-.037	-.0774	-4.95
CAR_{BUY}	13,091	.001	-.0192	0.38	2,227	-.054	-.0737	-7.38
CAR_{HOLD}	22,324	-.002	-.0180	-1.41	3,312	-.081	-.0922	-13.56
$CAR_{HOLD/SELL}$	3,876	-.023	-.0414	-5.05	430	-.090	-.1008	-5.50
$CAR_{STRONG\ SELL}$	2,626	-.023	-.0396	-4.44	286	-.122	-.1689	-6.05
National Brokerage Firm Analyst Recommendations								
$CAR_{STRONG\ BUY}$	5,049	.014	-.0074	4.0	540	-.048	-.0775	-3.2
CAR_{BUY}	6,152	.003	-.0147	0.8	657	-.030	-.0367	-2.3
CAR_{HOLD}	10,477	.000	-.0146	0.1	1,076	-.057	-.0683	-5.6
$CAR_{HOLD/SELL}$	1,866	-.016	-.0383	-2.5	145	-.120	-.1065	-4.4
$CAR_{STRONG\ SELL}$	731	-.042	-.0563	-3.9	58	-.099	-.1650	-2.3
Regional Brokerage Firm Analyst Recommendations								
$CAR_{STRONG\ BUY}$	7,503	.007	-.0139	2.6	1,587	-.034	-.0755	-3.6
CAR_{BUY}	5,237	.001	-.0227	0.2	1,376	-.066	-.0965	-6.9
CAR_{HOLD}	8,968	-.006	-.0225	-2.1	1,871	-.093	-.1038	-11.5
$CAR_{HOLD/SELL}$	1,400	-.024	-.0475	-3.2	209	-.092	-.1012	-3.9
$CAR_{STRONG\ SELL}$	1,546	-.013	-.0267	-2.0	195	-.137	-.1741	-5.6
Non-Brokerage Agency Analyst Recommendations								
$CAR_{STRONG\ BUY}$	1,267	-.011	-.0289	-1.6	199	-.038	-.0897	-1.6
CAR_{BUY}	1,702	-.005	-.0235	-0.8	194	-.052	-.0721	-2.1
CAR_{HOLD}	2,879	-.002	-.0180	-0.3	365	-.091	-.1032	-5.2
$CAR_{HOLD/SELL}$	610	-.040	-.0390	-3.4	76	-.030	-.0861	-0.8
$CAR_{STRONG\ SELL}$	349	-.030	-.0495	-2.1	33	-.071	-.1345	-1.1

This table presents the differential long-windowed security price changes associated with the five levels of analyst recommendations. The sample includes all July 1987 to July 1993 investment recommendations provided for the companies by 272 major brokerage firms and research institutions. *N* denotes the number of observations. *CAR* within window *[a, b]* denotes the market-model-beta-adjusted returns during event period [a, b], where day 0 is the analyst recommendation date. CAR_i denotes the market-model-beta-adjusted returns accompanying analyst recommendations with ranking i, where i = *STRONG BUY* when recommendation is *strong buy*; i=*BUY* when recommendation ranking is *buy/hold* or *weak buy*; i = *HOLD* when *hold* is recommended; i=*HOLD/SELL* when analyst recommended *hold/sell* or *weak sell*; i = *STRONG SELL* when *strong sell* is recommended. Benchmark period for estimating market-model beta: [-500,-250] U [+215, +339], where day 0 is the recommendation date.

Mean *CAR*s over event period [0, 150] reported in Panel B differ from the mean *CAR*s shown in Figures 1 and 2. It is because the latter data sets exclude observations with missing returns during the sixty days prior to the recommendations. However, these differences are not statistically significant.

Table 6(continued)

Panel B: Excess Returns Test Results with Sixty-One-Day ([0, 60]) Event Windows

	S & P 500 Firms				540 Non-S&P Firms			
	N	Mean	Median	T	N	Mean	Median	T
Overall Recommendations								
$CAR_{STRONG\ BUY}$	13,912	.011	.0017	9.24	2,405	.011	-.0076	2.38
CAR_{BUY}	13,169	.005	-.0046	3.92	2,305	-.002	-.0156	-0.48
CAR_{HOLD}	22,472	-.001	-.0094	-1.31	3,384	-.035	-.0420	-9.00
$CAR_{HOLD/SELL}$	3,923	-.012	-.0190	-4.61	435	-.049	-.0558	-4.69
$CAR_{STRONG\ SELL}$	2,648	-.016	-.0205	-5.14	292	-.064	-.0708	-4.78
National Brokerage Firm Analyst Recommendations								
$CAR_{STRONG\ BUY}$	5,076	.013	.0021	6.5	555	.003	-.0175	0.3
CAR_{BUY}	6,196	.007	-.0048	3.5	677	.011	-.0075	1.2
CAR_{HOLD}	10,538	-.001	-.0089	-0.8	1,095	-.026	-.0286	-3.9
$CAR_{HOLD/SELL}$	1,892	-.009	-.0190	-2.3	145	-.079	-.0714	-4.4
$CAR_{STRONG\ SELL}$	733	-.033	-.0354	-5.4	58	-.036	-.0722	-1.2
Regional Brokerage Firm Analyst Recommendations								
$CAR_{STRONG\ BUY}$	7,549	.012	.0033	7.4	1,645	.017	-.0014	2.9
CAR_{BUY}	5,268	.005	-.0042	2.6	1,431	-.006	-.0199	-1.0
CAR_{HOLD}	9,027	-.003	-.0128	-2.2	1,915	-.044	-.0472	-8.2
$CAR_{HOLD/SELL}$	1,412	-.018	-.0218	-4.2	213	-.043	-.0558	-2.9
$CAR_{STRONG\ SELL}$	1,561	-.009	-.0131	-2.2	199	-.075	-.0726	-4.5
Non-Brokerage Agency Analyst Recommendations								
$CAR_{STRONG\ BUY}$	1,287	-.001	-.0109	-0.3	205	-.010	-.0248	-0.6
CAR_{BUY}	1,705	-.002	-.0050	-0.5	197	-.020	-.0215	-1.5
CAR_{HOLD}	2,907	.005	-.0030	1.6	374	-.022	-.0487	-1.8
$CAR_{HOLD/SELL}$	619	-.009	-.0098	-1.3	77	-.011	-.0213	-0.4
$CAR_{STRONG\ SELL}$	354	-.012	-.0095	-1.4	35	-.047	-.0536	-1.3

Table 7
Company Size and Abnormal Trading Volume As Explanatory Variables to Post-Recommendation Cumulative Beta-Adjusted Returns

Panel A: Regression Model $CARPOSTREC_{[61,150]} = \beta_o + \beta_{SPCODE}\,SPCODE + \beta_{TA}\,TA + \beta_{AV}\,AV + \varepsilon$

	REC=*BUY*	REC=*HOLD*	REC=*SELL*
N	28,751	23,485	6,614
β_o	.000 (0.1)	-.010 (-2.7)	-.021 (-2.5)
β_{SPCODE}	.002 (0.5)	.015 (3.8)	.022 (2.6)
β_{TA}	.026 (5.8)	.023 (4.7)	.018 (2.1)
β_{AV}	-.018 (-14.8)	-.014 (-10.4)	-.012 (-4.6)
F-Value	104.4	69.1	15.2
Adjusted-R^2	0.011	0.009	0.006

Panel B: Regression Model $CARPOSTREC_{[4,150]} = \beta_o + \beta_{SPCODE}\,SPCODE + \beta_{TA}\,TA + \beta_{AV}\,AV + \varepsilon$

	REC=*BUY*	REC=*HOLD*	REC=*SELL*
N	28,710	23,468	6,612
β_o	.008 (1.8)	-.022 (-4.2)	-.058 (-4.9)
β_{SPCODE}	-.002 (-0.5)	.024 (4.4)	.045 (3.8)
β_{TA}	.039 (6.5)	.040 (5.9)	.027 (2.2)
β_{AV}	-.030 (-17.7)	-.027 (-14.8)	-.020 (-5.8)
F-Value	140.4	127.9	25.1
Adjusted-R^2	0.014	0.016	0.011

This table presents how abnormal trading volume surrounding an investment recommendation could help explain the security's post-announcement excess returns. The *BUY* test group consists of the shares that receive *strong buy* or *buy* recommendations. The *HOLD* test group consists of shares that are recommended to *hold*. The *SELL* group includes all securities that are given *strong sell* or *hold/sell* recommendations.

$CARPOSTREC_{[s,\ t]}$ denotes the post-recommendation cumulative market-model-beta-adjusted returns between days s and t, where day 0 is the recommendation date. The dummy variable *SPCODE* takes the value of 1 (0) if the company is (is not) a S & P 500 firm; *TA*, a control variable of firm size, denotes the concurrent year-end total asset of the company. The event window for *AV*, abnormal trading volume, is defined as 51 trading days centered around the recommendation date.

To the immediate right of each parameter estimate is the corresponding t-statistic.

Table 8
Type of Analyst As an Explanatory Variable to Post-Recommendation Cumulative Beta-Adjusted Returns

Panel A: Regression Model $CARPOSTREC_{[61,150]} = \beta_o + \beta_{SPCODE}\, SPCODE + \beta_{TA}\, TA + \beta_{NATCODE}\, NATCODE + \varepsilon$

	REC=*BUY*	REC=*HOLD*	REC=*SELL*
N	25,753	20,650	5,675
β_o	-.025 (-8.0)	-.027 (-7.1)	-.043 (-5.1)
β_{SPCODE}	.020 (5.8)	.024 (6.1)	.042 (4.8)
β_{TA}	.028 (6.1)	.024 (4.5)	.012 (1.3)
$\beta_{NATCODE}$	.004 (1.9)	.005 (1.9)	-.002 (-0.3)
F-Value	31.9	25.6	8.9
Adjusted-R^2	0.004	0.004	0.004

Panel B: Regression Model $CARPOSTREC_{[4,150]} = \beta_o + \beta_{SPCODE}\, SPCODE + \beta_{TA}\, TA + \beta_{NATCODE}\, NATCODE + \varepsilon$

	REC=*BUY*	REC=*HOLD*	REC=*SELL*
N	25,709	20,624	5,672
β_o	-.031 (-7.2)	-.059 (-11.4)	-.097 (-8.1)
β_{SPCODE}	.027 (5.8)	.045 (8.3)	.081 (6.5)
β_{TA}	.044 (6.8)	.044 (6.0)	.015 (1.2)
$\beta_{NATCODE}$	.004 (1.3)	.010 (2.7)	-.003 (-0.5)
F-Value	34.3	47.4	15.8
Adjusted-R^2	0.004	0.007	0.008

Panel C: Regression Model $CARPOSTREC_{[61,150]} = \beta_o + \beta_{SPCODE}\, SPCODE + \beta_{TA}\, TA + \beta_{BROCODE}\, BROCODE + \varepsilon$

	REC=*BUY*	REC=*HOLD*	REC=*SELL*
N	28,774	23,498	6,616
β_o	-.020 (-4.6)	-.034 (-7.0)	-.046 (-4.7)
β_{SPCODE}	.018 (5.7)	.028 (7.3)	.032 (3.8)
β_{TA}	.029 (6.5)	.026 (5.3)	.022 (2.5)
$\beta_{BROCODE}$	-.002 (-0.5)	.006 (1.7)	.010 (1.5)
F-Value	30.9	33.5	8.8
Adjusted-R^2	0.003	0.004	0.004

Table 8(continued)

Panel D: Regression Model $CARPOSTREC_{[4,150]} = \beta_o + \beta_{SPCODE}\, SPCODE + \beta_{TA}\, TA + \beta_{BROCODE}\, BROCODE + \varepsilon$

	REC=*BUY*	REC=*HOLD*	REC=*SELL*
N	28,722	23,470	6,612
β_o	-.031 (-5.1)	-.056 (-8.5)	-.098 (-7.2)
β_{SPCODE}	.025 (5.7)	.048 (9.4)	.063 (5.5)
β_{TA}	.044 (7.3)	.046 (6.8)	.032 (2.7)
$\beta_{BROCODE}$	.003 (0.6)	-.001 (-0.1)	.014 (1.4)
F-Value	35.0	53.7	14.6
Adjusted-R^2	0.004	0.007	0.006

This table shows whether the type of the research agency a security analyst belongs to (national-brokerage-firm, regional-brokerage-firm, or non-brokerage-agency) could help explain the post-announcement excess returns of the securities for which he recommends to buy, hold or sell. The *BUY* test group consists of the shares that receive *strong buy* or *buy* recommendations. The *HOLD* test group consists of shares that are recommended to *hold*. The *SELL* group includes all securities that are given *strong sell* or *hold/sell* recommendations.

$CARPOSTREC_{[s,\ t]}$ denotes the post-recommendation cumulative market-model-beta-adjusted returns between days s and t, where day 0 is the recommendation date. S&P classification code, *SPCODE*, takes the value of 1 (0) if the company is (is not) a S & P 500 firm. *TA*, a control variable of firm size, denotes the concurrent year-end total asset of the company. The dummy variable *NATCODE* takes the value of 1 (0) if the analyst making the recommendation belongs to a national (regional) brokerage firm. The dummy variable *BROCODE* takes the value of 1 (0) if the analyst belongs to a brokerage firm (non-brokerage agency).

To the immediate right of each parameter estimate is the corresponding t-statistic.

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Chapter 3: Security Analysts' Earnings Forecasts and Recommendations for Public Utility Firms

Abstract

This chapter examines security analysts' forecasts and recommendations for public utilities, investigating the extent conflicting pressure may help explain the variation in analysts' research reports. A maintained hypothesis of this study is that regulators are likely to lower rates if earnings prospects are too high. If so, then executives of utility firms may prefer that security analysts issue pessimistic earnings per share (EPS) forecasts. These executives, nevertheless, may still prefer optimistic recommendations. Although favorable recommendations are also observable to regulators, the coarseness and vagueness of recommendations are likely to limit the amount of information regulators may extract from them. As a consequence, conflicting pressure may result in analysts' biasing down their EPS forecasts without biasing down contemporaneous recommendations. This expected direction of bias contrasts with systematic optimism in both earnings forecasts and recommendations as documented in prior studies for industrial firms.

The empirical findings are consistent with the notion of reverse results of bias. First, by making inter-group comparison of 1988-92 earnings forecast errors between utility and non-utility firms, this study provides evidence that security analysts' earnings forecasts for utility (non-utility) firms are less (more) optimistic. Second, underwriter analysts appear to strategically bias their investment recommendations (earnings forecasts) upwards (downwards) for utility firms. Third, regression tests that investigate the influence of firms' profitability growth outlooks on underwriter-analysts' EPS growth estimates show that the difference between an underwriter analyst's and a comparison analyst's five-year EPS growth estimates for a utility becomes more pronounced as the underwriter analyst's growth estimate becomes greater.

1. Introduction

This study examines both analysts' forecasts and recommendations for utility firms, investigating the extent conflicting pressure may help explain the variation in analysts' investment recommendations.[1] Whereas all companies prefer favorable recommendations, not every corporate executive welcomes optimistic earnings forecasts. For fear that overly positive forecasts may induce regulatory interventions and thus jeopardize the firms' future profitability, utility firm executives may prefer to have analysts present lower forecasts of earnings. These executives, nevertheless, may still prefer optimistic recommendations. Although favorable recommendations are also observable to regulators, the coarseness and vagueness of recommendations are likely to limit the amount of information regulators may extract from them. As a consequence, conflicting pressure may result in analysts' biasing down their EPS forecasts without biasing down contemporaneous recommendations.

For public utilities, the threat of regulatory intervention is one of management's major concerns.[2] Regulatory agencies, most importantly the Public Utilities Commissions (hereafter the Commissions or the PUCs), play an ongoing and significant role in determining earnings of utility firms. Above all, the Commissions can enforce re-regulations or de-regulations, altering the firm's competitive environment. Moreover, a utility firm is required to reduce its current rates whenever it is regarded by the PUC as making excessive profits. Ultimately, without the PUCs' approval, utilities may not increase any rate or charge. The PUCs rarely accept utility firms' management forecasts as unbiased inputs to the rate setting processes. Julian Ajello, an official of the California Public Utilities Commission Energy Rate Design Division, commented on the estimates submitted for rate increase applications:

> "They always overestimate the expenses, underestimate the profits, and claim that their businesses are as risky as some much riskier [non-utility] firms. The PUC always needs to do its best to cut down the estimates of [the utilities'] operating expenses."[3]

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1 Incumbents that encounter potential threats of new entries in oligopoly industries are also likely to prefer unbiased or even downward biased earnings forecasts to optimistic ones.

2 See Donnelly (1992).

3 These remarks were made in a telephone interview the author conducted in March 1993 with Julian Ajello, director of California PUC Rate Design Division. The author also interviewed three major analysts for public utility firms: Linda Byus of Duff and Phelps, Steve Zimmermann of Standard and Poor's, and Robert Hornick of Fitch Investors Service.

Although analysts' EPS forecasts are not the only source of information about utility firms' current and future profits, the objectivity of these forecasts may be of great importance. As signals offered by seemingly independent sources, analysts' forecasts are often used as evidence in Commissions' cases to justify firms' accounting practices or management forecasts. For this reason, analysts' EPS forecasts may function differently in regulated versus unregulated industries. While upward revisions of analyst earnings forecasts for unregulated firms are generally favorable signals about firm values, large positive earnings forecast revisions may induce rejections of rate increase applications or other unfavorable regulatory interventions and thus jeopardize the utilities' future profitability.

Therefore, the expected direction of bias in analysts' EPS forecast for utility firms contrasts with that for industrial firms. Focusing on a cross-section of industries, prior studies by Lin and McNichols (1993a), Lin and McNichols (1993b), and Dugar and Nathan (1993) document that security analysts offer optimistic forecasts and recommendations for client companies. Nevertheless, public utility executives may prefer that analysts issue lower EPS forecasts.[4] Accordingly, if an analyst biases his report to maintain good relations with utility executives, he would systematically issue pessimistic earnings forecasts.

The predicted direction of bias also differs from what is proposed by Francis and Philbrick (1992), who documented that analysts' EPS forecasts are more optimistic for firms they assign *sell* (*hold*) rankings than for the ones they grant *hold* (*buy*) rankings. Their finding suggests that optimistic EPS forecasts help strategic analysts to maintain management relations, particularly for stocks with *sell* recommendations. In contrast, this study predicts that affiliated analysts would issue more pessimistic EPS forecasts regardless of their investment recommendations.

The empirical findings are consistent with a systematic difference between bias in earnings forecasts and recommendations. First, by making inter-group comparison of 1988-92 earnings forecast errors, this study provides evidence that analysts' forecasts for

4 By contending that utilities may understate their profitability, I do not intend to suggest that they over-charge rate payers. For instance, there may exist regulators who *always* make adjustments on the prospect measures prepared by firms or analysts to show their competence as rate watchers. According to Linda Byus, a major utility analyst of Duff and Phelps, many state regulators are not objective arbiters. She asserted in the March 1993 telephone survey with the author, "Utility regulations are political activities. And the PUCs are short-sighted. After all, the commissioners are appointed by governors." In this setting, it may be a *fair* equilibrium conduct that the firms always issue pessimistic estimates to the strategic commissioners.

utility (non-utility) firm earnings are less (more) optimistic.[5] Second, matched-pair difference analyses show that underwriter analysts (non-underwriter analysts) make more (less) pessimistic EPS forecasts and more (less) favorable investment recommendations for public utility firms.[6] Third, regression tests that investigate the influence of firms' profitability growth outlooks on underwriter-analysts' EPS growth estimates document that the difference between an underwriter analyst's and a comparison analyst's five-year EPS growth estimates for a utility becomes more pronounced as the underwriter analyst's growth estimate becomes greater.

2. Institutional Background

Privately-owned utility companies, including electric, gas, water, steam, sewer, pipeline, telephone and telegraph companies, and some transportation companies, are regulated by PUCs in the states they provide services. The Commissions have the authority to initiate investigations of specific issues that may lead to legislation, rate revisions, enforcement of lawful rates, and changes in rules or policies. Above all, without approval from the Commissions, a regulated utility may not increase any rate or charge.[7] As Joskow (1976) and Wolak (1992) emphasize, the public utility regulators' major goal is price-setting. One of the most common disputes in determining future rates concerns what the regulated firm's true operating costs are. Each regulated firm has private information, not known by the regulator, concerning its true costs of production.[8] In most instances, the utility has very little incentive to reveal this private information to the regulator. Moreover, as privately-owned companies that must answer to their shareholders, the utilities would use

5 For further preliminary evidence that analysts are least optimistic for these firms' EPS estimates, see O'Brien (1992), which listed both macroeconomic-factors-adjusted and unadjusted measures of analyst forecast bias (forecast error/price ratios) for seven major industries from December 1976 to June 1988 but did not examine what may contribute to the differences in bias across the industries.

6 A financial analyst is referred to as an underwriter-analyst for the company he follows if that company makes underwriting deals with the institution that employs him.

7 For further descriptions of PUCs' rate setting processes, see Appendix 1. Also, see California Public Utilities Commission (1987).

8 On the subject of price-setting, Alfred Sikes, the Chairman of the Federal Communication Commission, notes, "I don't believe that career government people, or for that matter career non-government people, can find out what the true cost of a service should be." (San Jose Mercury News, 1990).

this private information to maximize their profits subject to the constraints imposed by the regulatory process.

PUCs' rate decisions have two primary input variables, estimates of the utilities' prospects and the firms' prior-period performance. This study examines whether analyst forecasts are less optimistic for utilities than industrial firms. In contrast, Lin (1993b) investigates how PUCs' using earnings realizations for rate-settings affects the security price response to unexpected earnings and utility executives' incentives to manipulate reported income.

2.1 ESTIMATES OF PUBLIC UTILITY FIRMS' PROSPECTS

Each PUC starts the rate setting process by estimating a utility's reasonable expenses and revenues, then adding a "fair" rate of return on its investment. First, the Commission estimates the utility's future customer demands and operating expenses such as wages, taxes, supplies, and depreciation, often using the master data files submitted with the firm's rate change application as references. Second, the Commission computes the *rate base*, or the aggregate book value of the firm's plants and equipment devoted to public use. Finally, after examining the utility's interest on borrowed funds and dividends on preferred stock as well as exploring a reasonable allowance for a return on common equity, it determines the level of fair rate of return, namely, the fair percentage of returns to providers of the funds that support the *rate base*.

Analysts' forecasts often play significant roles in justifying utility firms' management forecasts. Although revenue and expense estimates account for substantial proportions of the materials submitted by utilities, the PUCs rarely accept these estimates as unbiased inputs to the rate setting processes. Instead, perceiving that utilities almost always (1) overestimate their expenses, (2) underestimate the profits, and (3) claim that their businesses are as risky as riskier non-utility firms, the PUCs often put discounts on estimates of expenses and make adjustments on parameters to the rate-profit functions.[9] When a utility company's estimates of expenses or revenues are not accepted by the PUC, or when its prudence in use of capital is challenged, the company can present statements made by independent parties to justify its management forecasts or executive decisions.

[9] Public utility analyst Linda Byus of Duff and Phelps told the author in the March 1993 telephone survey, "Utility firms never get everything they want in their rate change filings."

As third party experts, many security analysts following public utilities have either served as witnesses or provided forecasts as evidence in Commissions' cases.[10]

2.2 UTILITY FIRMS' PAST PERFORMANCE

The second factor that influences the magnitude of authorized future rate increases is the utilities' prior-period profit levels. Specifically, PUCs or rate normalization pressure groups may use large positive surprises of earnings realizations to support rate interventions against utility firms. In the rate-setting games between utilities and the PUCs, the firms are not necessarily the parties making the first moves. Instead, the PUCs frequently examine utilities' expense realizations, investigating whether their earnings levels are reasonable. If a firm's earnings realization is significantly greater than the authorized level, the PUC may bring in rate cases, requesting the utility to file rate reductions immediately.[11]

Lin (1993b) explores how PUCs' use of earnings realizations for rate-settings affects public utility investors' response to earnings surprises and utility firms' accounting practice. It documents that (1) for public utilities the relation between earnings and firm value is non-monotonic, and (2) public utilities with exceptionally good operating performance are systematically more conservative in capitalizing their interest expenditures for construction work. These results are consistent with the notion that large positive reported earnings may be used against the firms and thus may not be an unambiguously favorable signal to utility investors.

10 Some other utility analysts, on the other hand, choose not to take any positions in these cases. Standard and Poor's analyst Steven Zimmermann and Fitch Investors Service analyst Robert Hornick both told the author in the March 1993 telephone survey, "We don't take any positions since we are independent rating agencies."

11 Utilities' earnings measures also incorporate profits or losses from non-regulated operations. Ideally, earnings performance within non-regulated sectors should not affect PUCs' rate-making decisions. However, determining property, plant, and equipment for public use involves substantial information gathering efforts of cost allocations. There often exists some degree of subjectivity when the PUCs allocate the common resources within these firms. Robert Hornick, a major public utility analyst of Fitch Investors Services, told the author, "Rate setting decisions should be based on public utility capital and activities. But regulators may be subconsciously affected by the performance of these firms' non-regulated operations and use these items against these firms rate increase applications." Linda Byus of Duff and Phelps and Steven Zimmermann of Standard and Poor's both agreed with Mr. Hornick.

3. Analysts' EPS Forecasts and Recommendations As Signals for Utilities' Prospects

This section describes a "two-audience, two-signal" setting of how earnings forecasts and recommendations affect regulators and investors: investors may update their beliefs primarily based on analyst recommendations; regulators' rate-setting processes may be primarily affected by analyst EPS forecasts. While each audience is able to observe both signals, it may not be unambiguously cost-effective to eliminate the noise and use the other signal. Recognizing the relatively more (less) pronounced impacts of analyst recommendations (EPS forecast revisions) on investors' decisions and relatively more (less) significant influence of EPS forecast revisions (recommendations) on regulators' decisions, strategic executives may prefer a different direction of bias in these two signals. In cases where each of these two signals influences the decision making process of only one audience, analysts facing conflict of interest are unambiguously pressured into biasing down their EPS forecasts and biasing up their investment recommendations.[12]

3.1 ANALYSTS' EARNINGS FORECASTS

Analyst earnings forecasts for public utility firms serve as an indicator for monopoly profits. As signals provided by third party experts, these forecasts have strong potential for being adopted as evidence for or against the statements that a utility is earnings excess profits or that its management forecast is too low. For regulated firms, a large positive earnings forecast is not an unambiguously favorable signal. As it implies promising future prospects in the current regulatory environment, it also contributes to an increase in the likelihood that future rates may be lower. Therefore, utilities' future profitability may decline as analyst earnings forecasts increase.[13]

In contrast, utility investors, the second audience, may merely perceive EPS forecasts as a secondary factor for their investment decisions in the presence of analyst recommendations. For overall firms, as Chapter 2 demonstrates, analyst recommendations have much stronger impact on contemporaneous security returns than do analyst EPS

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12 As shown in Lin (1993b), if investors refer to analyst recommendations but ignore analyst EPS forecasts in determining whether to buy or sell the shares, then firm management would invariably favor optimistic recommendation ratings and lower EPS forecasts.

13 All of the March 1993 telephone survey participants agreed that exceptionally large earnings may hinder utilities' rate increase applications. They also stated that although analysts' EPS forecasts are not the only signal for future profits, these forecasts, as measures offered by seemingly independent sources, may be used as evidence in Commissions' cases to justify the firms' accounting practices and management forecasts.

forecast revisions. For public utility investors, the difference in relative informativeness between recommendations and EPS forecasts may be more evident.[14] As noted earlier, large positive analyst EPS forecasts may be a mixed signal. There may exist non-monotonic relations between firm values and earnings forecast revisions.

3.2 ANALYSTS' INVESTMENT RECOMMENDATIONS

Analysts' investment recommendations serve as a signal primarily to public utility investors for their decisions to buy, hold or sell shares. On the one hand, as guides to investment decisions, these ratings may more directly reflect analysts' price performance expectations on securities than analysts' earnings forecasts.

On the other hand, although analyst recommendations are also observable to regulatory agencies, they are, at best, a noisy measure that may be used to identify utilities' excess profitability. The PUCs, who aim at determining reasonable EPS estimates, would gain little efficiency by referring to recommendation ratings in the presence of analyst EPS forecasts. The coarseness and vagueness of recommendations are likely to limit the amount of information PUCs may extract from them for price-setting purposes. Above all, with only five levels of ratings, recommendations are a coarse signal for future earnings. Analysts' less frequent usage of the last two ratings, *hold/sell* and *strong sell*, may further confine regulators' inverting the future monopoly profit implication of these signals.

Moreover, vagueness is also a characteristic of analyst recommendations. First, analysts rarely specify their risk assessments and investment horizons. *Strong buy* recommendations merely signal high anticipated price levels relative to the current ones. There exists no indication as to whether the analysts expect a normal or an abnormal rate of return. Second, analysts' research reports provides no information regarding either the extent recommendation rankings are retrospective or the extent information regarding utilities' future profitability has been capitalized into *pre*-recommendation share prices.[15] Presumably, any security can be temporarily mispriced at any time, regardless of its past performance or future prospects. Without *explicit* indication as to whether and how a

[14] Regression analyses of contemporaneous abnormal returns versus analysts' EPS forecast revisions and recommendations for utilities provides evidence consistent with this notion.

[15] Consider the following extreme case: if (1) the existing price level reflects perfect foresight as to the future excess profits of a public utility firm, and (2) analyst recommendations are not retrospective, the firm should receive a *hold* rating even when the market *expects* it to incur monopoly profits in the future.

ranking decision corresponds to the security's current price level, it is dubious that the recommendation can serve as regulatory indicator for or against the utility.[16]

4. Hypotheses

As a consequence of the regulatory environment, the direction of bias in analyst earnings forecasts for public utilities may differ significantly from those for non-utility firms. Strategic executives of unregulated (regulated) companies are more (less) likely to favor optimistic earnings forecasts and may thus either coerce security analysts to issue more (less) positive reports or provide them with more (less) favorable news.

In this study, I first investigate whether analysts' EPS forecasts for public utilities are less optimistic than those for firms in other industries.

H_1: Security analysts' forecasts of earnings for utility firms are less optimistic than those for unregulated firms.

As Lin and McNichols (1993a), Lin and McNichols (1993b) and Dugar and Nathan (1993) suggest, maintaining client relationships may lead to misrepresentation in analysts' research reports. For public utilities, since EPS forecasts and recommendations may convey different information and may thus have a different primary audience, strategic underwriter analysts may choose to issue conservative EPS forecasts, which are more likely to be used as indicators by regulatory agencies, but to issue optimistic recommendations, which, as Chapter 2 documents, have more pronounced impact on contemporaneous security price movements. With this misrepresentation scheme, utilities can issue a favorable signal to investors without rendering adversarial evidence to rate regulators; furthermore, strategic underwriter-analysts can boost their underwriting profits without jeopardizing their relationships with corporate clients. Therefore, whereas Lin and McNichols (1993a) and Lin and McNichols (1993b) document optimistic underwriter analysts' EPS forecasts and recommendations for industrial firms, for utility firms, strategic underwriter-analysts are likely to release more favorable recommendation ratings but less positive earnings estimates.

By making matched-pair comparisons in analysts' EPS forecasts, recommendations and EPS growth estimates, I test the following hypotheses:

H_{2a}: Underwriter analysts' EPS forecasts for public utility firms are less optimistic than non-underwriter analysts' forecasts.

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[16] The market efficiency hypothesis predicts that no security can be mis-priced in one direction all the time.

H_{2b}: Underwriter analysts' investment recommendations for public utility firms are more favorable than non-underwriter analysts' recommendations.

H_{2c}: Underwriter analysts' five-year EPS growth estimates for public utilities are less optimistic than non-underwriter analysts' growth estimates.

Finally, utility firms' profitability growth outlooks may also influence underwriter-analysts' EPS growth estimates. Because utilities with stronger earnings prospects are more likely to be subject to regulators' rate deduction enforcement, I expect that utility firms with promising profitability growth may have stronger incentives to have affiliated analysts lower their EPS growth estimates than firms with gloomy outlooks. Specifically, I test the following hypothesis:

H_3: The difference between underwriter-analysts' and non-underwriter-analysts' EPS growth estimates for utilities is greater the greater the growth estimates provided by underwriter analysts.

5. Data

I conduct empirical tests of analysts' strategic behavior with two sample groups: an experimental group of public utilities and a comparison group of non-regulated Standard and Poor's 500 firms.[17] The test period for this chapter is from 1988 to 1992.

There are six sets of data items used in investigating analysts' forecast and recommendation bias: analyst multiple-year earnings estimates and earnings growth estimates, data on analysts' recommendation ratings, companies' annual and quarterly earnings, companies' number of shares outstanding, security prices, and data on public offerings of equity securities. Data on analyst research reports (names of forecasting agencies, earnings forecasts, five-year EPS growth estimates, recommendation ratings, and estimate/recommendation dates) are provided by Research Holdings Limited, Standard and Poor's Earnings Forecaster, and the Wall Street Transcript. Also, I retrieved annual and quarterly earnings per share measures from the Industrial COMPUSTAT tape. Data on distribution factors and split dates for events of changes in number of shares such as stock split and stock dividends and security returns for firms listed on NYSE/AMEX or NASDAQ are provided by the CRSP tape; data on equity security offerings (offering dates, amounts, names of managers, and fees) are collected from the Security Data

[17] This study classifies regulated industries with the same definition used in O'Brien and Bhushan (1990). Specifically, these are Trucking, Broadcasting, Utility Services, Savings Institutions, Security Brokers, Insurance, Nursing and Personal Care, and Health. These industries are required to submit detailed reports to regulatory agencies.

Company, Inc. Public Offering database, the Securities Exchange Commission Registration and Offering Statistics File, and the Corporate Finance Sourcebook.

6. Research Design and Test Results

6.1 ANALYSTS' EPS FORECASTS FOR UTILITY VERSUS NON-UTILITY FIRMS

To test Hypothesis 1, this section conducts two-sample tests of analysts' EPS forecast errors.

As discussed earlier, public utilities' preference for bias in earnings forecasts may differ from that of non-utility firms'. Whereas industrial firm management may prefer optimistic earnings forecasts, for fear of regulatory interventions, utility firm executives may either coerce security analysts to issue less optimistic EPS forecasts or provide the analysts with unfavorable news about the firms' future profitability.[18]

To investigate whether this difference in executive preference results in differential security analysts' EPS forecast bias, I make inter-group comparisons for 1988-92 security-price-deflated earnings forecast errors. If the two-sample test statistics for the difference between utility and non-utility firms' mean forecast errors were significantly negative, it would be consistent with Hypothesis 1.

Table 1 reports the test results. It shows that security analysts over-estimated both utility and non-utility firms' one-year-ahead earnings during 1988-92. Moreover, it reports that, for both *S & P 500* and *Non-S&P* test groups, comparison test t-statistics as well as non-parametric Wilcoxon z-statistics and Kruskal-Wallis χ^2 statistics are all significant at 0.005 level. These findings suggest that overall analyst earnings forecasts for utilities are less optimistic than those for non-utilities.[19]

6.2 EPS FORECASTS, RECOMMENDATIONS AND EPS GROWTH ESTIMATES BY UNDERWRITER VERSUS NON-UNDERWRITER ANALYSTS

This section explores whether underwriter analysts release lower (more optimistic) forecasts of earnings (investment recommendations) for public utility firms. As shown in

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[18] Namely, in their disclosures to analysts, these companies' understate their current and anticipated prospects.

[19] A competing explanation to less optimistic forecasts of utilities' earnings is that utilities (non-utility firms) experienced systematically more favorable (less favorable) unanticipated earnings during the test period. This potential motivates my research work reported in Sections 6.2 and 6.3. These sections partition analysts' forecasts and investment recommendations by the degree of their brokerage firms' involvement in underwriting for that company and adopt match-pair difference tests to further identify analysts' strategic reporting behavior.

Chapter 2, all security analysts may encounter conflicting pressure to provide biased forecasts or recommendations to maintain good relationships with corporate executives. Affiliated analysts, nevertheless, may have stronger incentives to curry favor with the client company executives who prefer biased research reports than do unaffiliated analysts.[20] Via matched-paired design, I find empirical results consistent with the hypothesis of strategic reporting.[21] The difference tests provide evidence that underwriter analysts tend to make more pessimistic EPS forecasts and more favorable investment recommendations for public utility firms. They also provide weak evidence that underwriter (non-underwriter) analysts' EPS growth estimates are more (less) pessimistic.

First, I test the hypothesis that underwriter analyst earnings forecasts are less optimistic via matched pairs of underwriter-analyst forecasts and comparison forecasts made closest to the underwriter analyst estimate dates.[22] If affiliated analysts bias their reports strategically to curry favor with the issuing firms, then we would expect their EPS forecasts to be systematically less than non-underwriter analysts'; their investment recommendations would be systematically more favorable than non-underwriter analysts'.

Table 2 presents the test results. Panel A (B) shows that the results of tests focusing on forecast differences between underwriter and non-underwriter analysts' one-year- (two-year-) ahead EPS forecasts issued immediately prior to equity offerings.[23] Consistent with the strategic misrepresentation hypothesis, underwriter analysts' earnings

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20 This incentive problem may result from (1) that underwriter analysts work closely with the issuing firms and value this monopolistic access to firm-specific information, or (2) that underwriter analysts do not want to jeopardize the firms' business relationship with the companies.

21 The matched-pair research design helps mitigate a potential limitation to empirical studies concerning specific consensus analyst forecasts during any short test period. As Brown, Foster and Noreen (1985) indicate, there exists lack of reliability as inferences about whether these forecasts are unbiased estimates of the actual EPS. There are periods in which the whole economy or an industry grows faster than expected and periods in which most companies suffer from unanticipated poor performance.

22 This test method is also used in Lin and McNichols (1993a) and Lin and McNichols (1993b).

23 These tests (Panels A and B of Table 2) includes an observation of underwriter analysts' EPS forecast in the samples if and only if it is issued within three-hundred calendar days prior to an equity offering. Likewise, Panels A and B of Table 3 include an underwriter analysts' investment recommendation in the samples if and only if it is issued within three-hundred calendar days prior to an equity offering date. As specification checks, for tests reported in Panels C and D of Table 2 as well as Panel C of Table 3, I disregard the differences in time between forecasts or recommendations and public offering and include the five closest EPS forecasts or recommendations surrounding each underwriting event.

forecasts appear to be significantly less than non-underwriter analysts'. Moreover, Panels C and D show that these results are robust with respect to a different research design that includes the five closest underwriter-analysts' EPS forecasts as experimental observations.[24] Underwriter (non-underwriter) analysts appear to make more pessimistic (optimistic) earnings forecasts.

Second, this study tests the hypothesis that underwriter analyst investment recommendations are more optimistic by matching underwriter-analyst recommendations and comparison recommendations made closest to the underwriter analyst recommendation dates. To examine the robustness of the results regarding differential selection criteria, I conduct difference tests with three various benchmarks for including experimental and control observations. Table 3 reports the results of ranking difference tests, presenting that underwriter (non-underwriter) analysts recommend more (less) favorably. Also, consistent with the notion that brokerage analysts encounter heavier pressure from corporate management than non-brokerage analysts, this table shows that underwriter analysts provide more optimistic recommendations than both Standard and Poor and Value Line comparison analysts.

Third, I conduct match-paired difference tests of whether underwriter (non-underwriter) analysts provide less (more) optimistic five-year earnings growth estimates. To test Hypothesis 3a, I examine the difference between underwriter analysts' five-year EPS growth estimates and the comparison estimate closest in time, and made within 180 days surrounding the underwriter analysts' EPS growth estimate date. As Panel A of Table 4 reports, the mean difference between underwriter and non-underwriter analysts' EPS growth estimates is negative for the overall utility sample. However, the t-statistic is only marginally significant. To secure further evidence for making stronger inferences regarding differences in analyst EPS growth estimates, I conduct tests reported in Section 6.3.

6.3. GROWTH PROSPECTS AS AN EXPLANATORY VARIABLE FOR DIFFERENCES IN EPS GROWTH ESTIMATES

This section investigates how utility firms' profitability growth outlooks influence underwriter-analysts' EPS growth estimates. Because utilities with stronger growth

[24] The research design of these tests, as well as that for the tests reported in Panel C of Table 3, increases the sample size by more than five times, since it does not exclude observations with analyst EPS forecasts (analyst recommendations) older than three hundred days as of the public offering dates.

potential are more likely to be subject to regulators' rate reduction efforts, I expect that utility firms with a more promising (gloomy) profitability growth outlook may have greater (lesser) incentive to have affiliated analysts lower their EPS growth estimates. Regression analyses in this section provide evidence consistent with the strategic reporting hypothesis, in that the greater the five-year EPS growth estimates provided by underwriter-analysts, the more pessimistic these analysts' growth estimates are.

To test Hypothesis 3, I regress the difference between underwriter and comparison analysts' five-year earnings per share growth estimates on underwriter analysts' five-year growth estimates. Panel B of Table 4 reports the test results. It shows that, for the public utility sample, when either non-underwriter or co-underwriter analysts' growth estimates serve as the comparison observations, the difference between an underwriter analyst's and a comparison analyst's five-year EPS growth estimate for a utility is more pronounced the greater the underwriter analyst's growth estimate. The t-statistics for the slope coefficient estimates are negative and significant for both cases. These results contrasts with the findings for non-utility S & P 500 firms. For the non-utility control test group, both t-statistics are significantly positive.[25]

7. Discussion and Extension

In this chapter, I conduct a joint examination of analysts' recommendations and EPS forecasts for public utilities to further explore analysts' role as users and producers of firm-specific information. Because regulators are likely to lower rates if earnings prospects are too high, executives of utility firms have an incentive to coerce analysts to issue pessimistic EPS forecasts. This expected direction of bias contrasts with systematic optimism in both EPS forecasts and recommendations as prior studies documented for industrial firms.

This chapter provides evidence as to the extent conflicting pressure may explain the variability of analysts' investment recommendations. First, by making inter-group comparison of 1988-92 earnings forecast errors between utility and non-utility firms, this study provides evidence that security analysts' earnings forecasts for utility (non-utility) firms are less (more) optimistic. Second, underwriter analysts appear to strategically bias their investment recommendations (earnings forecasts) upward (downward) for utility

[25] If there exist extreme estimates provided by underwriter analysts, this research design may be biased against rejecting the null hypothesis of no estimate difference. After all, the dependent variable may be viewed as underwriter analysts' estimate minus comparison estimate. Therefore, it may be difficult to explain why there may exist positive slope coefficients for the control test group .

firms. Third, regression tests investigating the influence of firms' growth outlooks on underwriter-analysts' EPS growth estimates present that the difference between an underwriter analyst's and a comparison analyst's five-year EPS growth estimates for a utility is more pronounced the greater the underwriter analyst's growth estimate.[26]

This study also suggests a few areas for future work. Above all, future research could replicate the tests in this study for firms in oligopolistic industries.[27] Because potential rivals are likely to enter and dampen existing firms' future profitability if and only if the incumbents' earnings prospects are high, incumbent firm executives may prefer pessimistic analysts' EPS forecasts *and* recommendations.

Moreover, under the threat of regulatory intervention, utility firms may have incentives to discount their reported profits. In future research, I plan to examine these firms' discretionary accruals, investigating (1) whether utilities adopt more conservative accounting practices, and (2) how these firms' accounting methods change during periods of intensifying competition or regulatory intervention. I also plan to study these firms' management compensation packages. Assuming (1) that utility firm values do not always increase with their reported earnings, and (2) that it is in investors' interests that utility executives avoid large positive earnings surprises, the examination could focus on the following two aspects: First, to assert that public utility management prefers unduly conservative accounting numbers, one needs a presumption that either firm value maximization or other consequences of accounting earnings are among these executives' major objectives. I expect that public utility top managers' pecuniary rewards are more closely associated with stock price performance as opposed to current firm earnings. Second, I will investigate whether these firms apply upper bounds on earnings in their bonus contracts. Healy (1985) contended that firms adopt such upper limits to create an incentive for the managers to increase dividend payments when the upper limit is binding, thereby counteracting potential over-retention problems. Still, there could be another plausible explanation for such phenomenon. Namely, firms set these upper bounds to mitigate the accrual policies that would result in exceptionally large earnings. In an extension to this study, I plan to investigate whether there is a greater frequency of upper-bounds for bonus in utilities' compensation packages.

[26] Similar behavior is also expected in other regulated companies and (in oligopoly industries) incumbent firms facing substantial pressure of potential entries. For the latter set of firms, the threats of potential entries may have effects similar to the threats of regulatory interventions.

27 The rivals would enter only if the prosperity exceeds a certain level, since they have capital constraints and entry costs.

Finally, the result of comparative static analyses suggest that a firm's cost of capital, the level of EPS considered as reasonable by the regulatory body, as well as the potential functional form of the probability of regulatory intervention could all affect these firms' earning-value relation. An interesting extension to this study would be an empirical examination of the impacts of these factors.

Appendix 1

The Commissions set rates in three primary ways: through general rate cases, through offset proceedings -- both of which result from applications filed by the utilities -- and through advanced letter filings. General rate cases have been the most common regulatory proceedings. In a general rate case, when a utility files to seek a general rate increase, it files a Notice of Intent (NOI) with the PUC. This contains working data in support of its eventual applications. An application is filed thirty days later. When received the applications, the Commissions take a thorough look at the utilities' financial pictures. The Commissions' Public Staff Division (PSD) examines factors such as the quality of service, prudence of management decisions, and effectiveness of conservation programs. Then based on its responsibility to look after the long-term interest of rate-payers, the PSD makes its recommendations to the Commission. General rate applications for major utilities may be filed every three years and take about a year to complete. In the process, a major guideline stated by all PUCs is to be fair both to consumers and to utility stockholders.

While most elements of rate-making can be predicted in a general rate case, a few elements can change substantially between general rate cases. Offset procedures have been designed to enable utilities to keep pace with changing costs, in the intervals between general rate cases, through rate adjustments to offset changes in those costs. Thus through rates, the public utilities could recover the exact amount of the increase expenses that they have experienced.

The third primary way the PUCs set rates, the advice letter procedure, is used extensively by small utility firms (e.g., in California, a certain small-sized telephone companies and any utility firms with estimated annual operating revenues no greater than $750,000.) These proceedings do not normally involve public hearings. The companies would merely need to include facts justifying the increases in the letter.

Table 1
Two-Sample Tests of Bias in 1988-1992 Analyst Fy1 Earnings Forecasts between Public Utilities and Non-Utility Firms

Panel A: Within the Standard & Poor's 500 Test Group

	Public Utility Firms			Non-Utility Firms		
	N	Mean	STD.DEV.	N	Mean	STD.DEV.
Full Samples	9184	-0.026	0.094	104329	-0.031	0.151
Reduced Samples	9169	-0.026	0.092	101679	-0.028	0.086

	Two-Sample T-Test		Wilcoxon		Kruskal-Wallis	
	T-statistic	Prob>|T|	Z-statistic	Prob>|Z|	χ^2	Prob> χ^2
Full Samples	5.20	0.0001	5.82	0.0000	33.93	0.0001
Reduced Samples	1.70	0.0888	8.28	0.0000	68.50	0.0001

This table presents the results of my two-sample tests of bias in 1988-1992 analyst Fy1 earnings forecasts (forecast error/price ratios) between public utilities and non-utility firms. Panel A (B) includes the comparison test results for the *S & P 500* (*Non-S&P*) test group.

In order to investigate whether the results are robust with respect to exclusion of influential observations, I adopt both full and reduced samples for each test group. Note that the non-utility samples have very extreme standard deviations of price-deflated forecast errors for both *S & P 500* and *Non-S&P* test groups. Also, the full sample for *Non-S&P* non-utilities appear to have extreme mean forecast error/price ratio. Thus I repeat the two-sample tests with (1) observations with either absolute EPS realizations or absolute EPS estimates greater than the price deflators, and (2) observations with price-deflated Fy1 forecast errors within either the top 1% or the bottom 1%, excluded. Nevertheless, the results of my two-sample tests conducted with the reduced samples, as well as the non-parametric z and χ^2 statistics for the full samples, suggest that my significant test results for the full samples are not due to extreme observations.

Table 1(continued)

Panel B: Within the Group of 540 Randomly Selected Non-S&P 500 Firms

	Public Utility Firms			Non-Utility Firms		
	N	Mean	STD.DEV.	N	Mean	STD.DEV.
Full Samples	1597	-0.031	0.085	18257	-0.246	10.234
Reduced Samples	1560	-0.034	0.076	17146	-0.039	0.118

	Two-Sample T-Test		Wilcoxon		Kruskal-Wallis	
	T-statistic	Prob>|T|	Z-statistic	Prob>|Z|	χ^2	Prob> χ^2
Full Samples	2.84	0.0045	5.18	0.0000	26.86	0.0001
Reduced Samples	2.46	0.0139	4.89	0.0000	23.90	0.0001

Table 2
Differences between Lead Underwriter Analysts' and Comparison Earnings Forecasts for Utility Companies

	N	Mean	Median	Standard Deviation	t-statistic	Sign Test z-statistic
Panel A: Differences in Forecasts of Current Year Earnings						
$DIFF_{uw,no}$	29	-0.042	-0.028	0.051	-4.48	-3.40
$DIFF_{uw,sp}$	17	-0.038	0.000	0.075	-2.12	-1.67
$DIFF_{uw,co}$	17	-0.023	0.000	0.084	-1.12	-1.00
Panel B: Differences in Forecasts of Subsequent Year Earnings						
$DIFF_{uw,no}$	45	-0.024	-0.026	0.059	-2.66	-1.94
$DIFF_{uw,sp}$	13	-0.011	0.010	0.082	-0.50	0.28
$DIFF_{uw,co}$	19	-0.029	-0.029	0.092	-1.39	-1.41
Panel C: Differences in Forecasts of Current Year Earnings (Two Most Recent Underwriter Forecasts Made Prior to the Offering Date, Underwriter Forecast on Offering Date, Two Underwriter Forecasts Immediately after Offering Date)						
$DIFF_{uw,no}$	269	-0.015	-0.001	0.100	-2.48	-2.00
$DIFF_{uw,sp}$	143	-0.014	0.000	0.109	-1.59	-2.99
$DIFF_{uw,co}$	155	-0.009	0.000	0.231	-0.51	0.64
Panel D: Differences in Forecasts of Subsequent Year Earnings (Two Most Recent Underwriter Forecasts Made Prior to the Offering Date, Underwriter Forecast on Offering Date, Two Underwriter Forecasts Immediately after Offering Date)						
$DIFF_{uw,no}$	277	-0.025	-0.016	0.181	-2.28	-3.12
$DIFF_{uw,sp}$	72	-0.013	0.000	0.086	-1.26	-0.62
$DIFF_{uw,co}$	144	0.025	-0.022	0.457	0.67	-3.24

$DIFF_{uw,no}$: Lead Underwriter less Non-Underwriter Analysts' earnings Forecasts, Deflated by Non-Underwriter Analysts' earnings Forecast.

$DIFF_{uw,sp}$: Lead Underwriter less Standard & Poor Earnings Forecasts, Deflated by Standard & Poor Earnings Forecast.

$DIFF_{uw,co}$: Lead Underwriter less Co-Underwriter Analysts' Earnings Forecasts, Deflated by Co-Underwriter Analysts' earnings Forecast.

Table 3
Differences between Lead Underwriter Analysts' and Comparison Investment Recommendations for Utility Companies

Panel A: Underwriter Analysts' Recommendations vs. Comparison Recommendations Made Closest in Time

	N	Mean	Median	Standard Deviation	t-statistic	Sign Test z-statistic
$DIFFA_{uw,no}$	69	-0.273	0.000	1.102	-2.06	-1.29
$DIFFA_{uw,sp}$	51	-0.667	-1.000	1.291	-3.69	-3.24
$DIFFA_{uw,co}$	54	-0.333	0.000	1.009	-2.43	-2.67

Panel B: Underwriter Analysts' Recommendations vs. Comparison Recommendations Made Closest in Time, And within 90 days (Non-Underwriter or Co-Underwriter Recommendations As the Controls) or 240 Days (Standard and Poor's Recommendations As the Controls) Surrounding the Underwriters' Recommendation Dates

	N	Mean	Median	Standard Deviation	t-statistic	Sign Test z-statistic
$DIFFB_{uw,no}$	61	-0.147	0.000	0.928	-1.24	-0.87
$DIFFB_{uw,sp}$	9	-0.889	-1.000	0.782	-3.41	-2.45
$DIFFB_{uw,co}$	16	-0.313	0.000	1.078	-1.16	-1.26

Table 3(continued)

Panel C: Underwriter Analysts' Recommendations (Two Most Recent Recommendations Prior to the Offering Date, Recommendation on Offering Date, Two Recommendations Immediately after Offering Date) vs. Comparison Recommendations Made Closest in Time, And within 90 days (Non-Underwriter or Co-Underwriter Recommendations As the Controls) or 240 Days (Standard and Poor's Recommendations As the Controls) Surrounding the Underwriters' Recommendation Dates

	N	Mean	Median	Standard Deviation	t-statistic	Sign Test z-statistic
$DIFFC_{uw,no}$	137	-0.238	-0.250	1.110	-2.50	-2.70
$DIFFC_{uw,sp}$	25	-0.800	-1.000	0.866	-4.62	-3.50
$DIFFC_{uw,vl}$	25	-0.840	-1.000	0.987	-4.26	-3.15
$DIFFC_{uw,co}$	39	-0.449	0.000	0.858	-3.27	-2.84

$DIFFA_{uw,no}$: Lead Underwriter less Non-Underwriter Analysts' Recommendations Made Closest in Time.
$DIFFA_{uw,sp}$: Lead Underwriter less Standard & Poor Recommendations Made Closest in Time.
$DIFFA_{uw,co}$: Lead Underwriter less Co-Underwriter Analysts' Recommendations Made Closest in Time.
$DIFFB_{uw,no}$: Lead Underwriter less Non-Underwriter Analysts' Recommendations Made Closest in Time, And within 90 Days Surrounding the Underwriter's Recommendation Date.
$DIFFB_{uw,sp}$: Lead Underwriter less Standard & Poor Recommendations Made Closest in Time, And within 240 Days Surrounding the Underwriter's Recommendation Date.
$DIFFB_{uw,co}$: Lead Underwriter less Co-Underwriter Analysts' Recommendations Made Closest in Time, and within 90 Days Surrounding the Underwriter's Recommendation Date.
$DIFFC_{uw,no}$: Lead Underwriter less Non-Underwriter Analysts' Recommendations Made Closest in Time.
$DIFFC_{uw,sp}$: Lead Underwriter less Standard & Poor Recommendations Made Closest in Time.
$DIFFC_{uw,vl}$: Lead Underwriter less Value Line Recommendations Made Closest in Time.
$DIFFC_{uw,co}$: Lead Underwriter less Co-Underwriter Analysts' Recommendations Made Closest in Time.

Table 4
Underwriter versus Comparison Analysts' EPS Growth Estimates for Public Utilities

Panel A: Underwriter Analysts' Five-Year EPS Growth Estimates vs. Comparison Estimates Made Closest in Time, and within 180 days Surrounding the Underwriters' Estimate Dates

	N	Mean	Median	Standard Deviation	t-statistic	Sign Test z-statistic
Overall Sample for Public Utility Firms						
$DIFFG_{uw,no}$	49	-0.014	0.000	0.059	-1.70	-0.45
$DIFFG_{uw,co}$	28	-0.015	0.005	0.069	-1.16	0.82
Observations with Underwriter Growth Estimates Less Than or Equal to the Median Estimate						
$DIFFG_{uw,no}$	19	-0.002	0.004	0.019	-0.46	0.47
$DIFFG_{uw,co}$	13	0.000	0.010	0.031	0.02	0.83
Observations with Underwriter Growth Estimates Greater Than the Median Estimate						
$DIFFG_{uw,no}$	30	-0.022	-0.005	0.073	-1.65	-0.96
$DIFFG_{uw,co}$	15	-0.027	0.000	0.089	-1.19	0.30

Table 4(continued)

Panel B: Linear Regression Tests: Lead Underwriter Analysts' Five-Year EPS Growth Estimate As an Explanatory Variable to Underwriter Analysts' Growth Estimate Deviations

Group	N	F-Value	Adj-R2	b_o	$T{:}b_o=0$	b_1	$T{:}b_1=0$
Model $DIFFG_{uw,no} = \beta_o + \beta_1 * LGro$							
Utili	49	15.510	0.232	0.022	1.89	-0.491	-3.94
SP500	41	11.326	0.205	-0.058	-2.86	0.394	3.37
Model $DIFFG_{uw,co} = \beta_o + \beta_1 * LGro$							
Utili	28	9.054	0.230	0.027	1.51	-0.584	-3.01
SP500	14	7.049	0.318	-0.075	-1.65	0.645	2.66

$DIFFG_{uw,no}$: Lead Underwriter less All Non-Underwriter (Investment Bank and Non-Investment-Bank Research Firm) Analysts' Five-Year EPS Growth Estimates Made Closest in Time, and within 180 Days Surrounding the Underwriter's Estimate Date.

$DIFFG_{uw,co}$: Lead Underwriter less Co-Underwriter Analysts' Five-Year EPS Growth Estimates Made Closest in Time, and within 180 Days Surrounding the Underwriter's Estimate Date.

LGro: Lead-Underwriter Analyst's Five-Year EPS Growth Estimate.

Utili: Utility Firms.

SP500: Non-Utility Standard & Poor's 500 Firms.

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