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Are Markets Rational? Investors' Response to Persistent Bias in Analysts' Earnings Forecasts

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To the Graduate Council:

I am submitting herewith a dissertation written by Seung-Woog Kwag entitled "Are Markets Rational? Investors' Response to Persistent Bias in Analysts' Earnings Forecasts." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Business Administration.

Dr. Ronald E. Shrieves, Major Professor

We have read this dissertation and recommend its acceptance:

Dr. James W. Wansley, Dr. M. Cary Collins, Dr. Bruce K. Behn

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(Original signatures are on file with official student records.)

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Are Markets Rational?

Investors' Response to Persistent Bias in Analysts' Earnings Forecasts

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Seung-Woog Kwag

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DEDICATION

This dissertation is dedicated to my parents, Jung-Bun Won and Tae-Hak Kwag,

my parents-in-law, In-Ja Kim and Eung-Shim Kei,

my wife and daughters, Youngmi Kei, Daun Kwag, and Doyoung Kwag,

and my brothers and sister,

for always believing in me, bringing happiness into my life,

and encouraging me to reach higher.

Life is beautiful with love from my family.

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ABSTRACT

This dissertation intends to address the following two issues: 1) Persistence of the bias in analysts' earnings forecasts; 2) Investors’ response to such bias. It extends the understanding of information economics in earnings studies, and is expected to improve asset pricing models, suggest better model specifications for earnings studies, provide regulatory policy implications, and facilitate discussions on investor rationality.

Using two look-back portfolio formation methods that capture salient features of analysts' past forecasting behavior, I form quintile portfolios that describe the range of analysts' forecasting behavior. The optimistic portfolios refer to the portfolios containing firm-quarters whose contemporaneous forecast errors are likely to be negative, while the pessimistic portfolios refer to the portfolios containing firm-quarters whose contemporaneous forecast errors are likely to be positive. Evidence that the two formation methods have significant predictive power for the contemporaneous forecast errors is found and this suggests that there is persistent bias in analysts’ earnings forecasts.

Investors’ response to the persistent bias is characterized by two hypotheses. The naïve expectations hypothesis (*NEH*) predicts that investors naively follow analysts’ past forecasting behavior, while the rational expectations hypothesis (*REH*) predicts that investors fully adjust for analysts’ past forecasting behavior when investors form their own expectations about contemporaneous earnings.

Major findings are reported regarding behaviors of two market participants – financial analysts and investors – in forming their expectations in quarterly earnings. The first set of findings provides strong evidence of persistent bias in analysts' forecasts. The second set of findings suggests that investors’ reaction to analysts’ forecasting behavior is complex. The data does not strongly reject the *NEH* in favor of the *REH*. It is speculated that investors sometimes seem neither naïve nor rational. Rather, they seem to possess another type of quasi-rational behavior other than naïve. As a result, the simple framework (*NEH* versus *REH*) used in this dissertation has a limit. The examination of a full range of investor behavior is encouraged for future research.

Chapter 1

Introduction

1.1 Overview

> Behavioral finance is no longer as controversial a subject as it once was. As financial economists become accustomed to thinking about the role of human behavior in driving stock prices, people will look back at the articles published in the past 15 years and wonder what the fuss was about. I predict that in the not-too-distant future, the term "behavioral finance" will be correctly viewed as a redundant phrase. What other kind of finance is there? In their enlightenment, economists will routinely incorporate as much "behavior" into their models as they observe in the real world. After all, to do otherwise would be irrational [Thaler (1999; p. 16)].

In the real world, two groups of market participants – rational and quasi-rational – coexist.[1] If the quasi-rational participants dominate the rational ones in the market decision-making process, rational market equilibrium is unlikely to be achieved. For example, if analysts behave quasi-rationally due to certain economic incentives or non-economic behavior when they forecast earnings, then their earnings forecasts are likely to show systematic patterns – overreaction, underreaction, optimism, or pessimism – as reported in a wealth of finance and accounting literature.

Currently, there are two basic alternative explanations for analysts' earnings forecasting behavior – one based on response to economic incentives and the other based on non-economic behavior. Some argue that economic incentives may influence

[1] Thaler (1986) defines quasi-rational behavior as behavior that is "purposeful, regular, and yet systematically different from the axioms of economic theory" (p. S280). Thus, he argues that "someone

analysts' earnings forecasts because of analysts' underwriting relationships with companies whose earnings they are forecasting, career (reputation) concerns, or earnings management by companies being analyzed [Scharfstein and Stein (1990); Dechow, Hutton, and Sloan (1998); Michaely and Womack (1999); Degeorge, Patel, and Zeckhauser (1999); Lim (2000)].

The second group of explanations draws from behavioral scientists and financial economists to suggest that individuals do not tend to follow the statistical theory of prediction.[2] Rather, individuals use their own subjective probability of an event (e.g., unexpected earnings information) to determine their response to the event [Kahneman and Tversky (1972, 1973); Tversky and Kahneman (1973); Einhorn and Hogarth (1985)].[3] A wealth of behavioral finance literature has reported that there exist behavioral tendencies in both analysts' and investors' reactions to unexpected earnings information. In the context of reactions to earnings information, such behavioral tendencies of analysts and/or investors have been characterized as overreaction, underreaction, or optimism [De

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who systematically overreacts to new information in violation of Bayes' rule is predictable yet only quasi-rational" (p. S281). In this paper, the market participants of interest are financial analysts and investors.

[2] The statistical theory of prediction refers to the normative (Bayesian) approach in which probability can be operationally defined via choices among events. If two events provide identical payoffs but one is preferred to the other, it follows that the probability of winning is greater for the chosen alternative. According to Kahneman and Tversky (1973), the statistical theory of prediction involves three types of information: prior information, specific evidence concerning the individual case, and the expected accuracy of prediction.

[3] As in Kahneman and Tversky (1972; p. 431), as opposed to the Bayesian probability (or objective probability) of an event, "subjective probability of an event" is defined as any estimate of the probability of an event that is provided by a subject, or represented by his or her behavior. Unlike the statistical theory of prediction (the Bayesian probability), the subjective probability relies not on prior probability but on a judgmental heuristic called representativeness [Kahneman and Tversky (1972, 1973)]. This approach predicts that a person, in many cases, judges that an event is more probable than another whenever the former appears to represent both the population proportion and the randomness of the process. For example, when a group of subjects are given the sequence of coin tosses, more subjects document that HTTHTH is more probable than either HHHHTH or HHHTTT, although all three sequences have the same prior probabilities [Tversky and Kahneman (1973); also see Einhorn and Hogarth (1985) for a similar example].

Bondt and Thaler (1985, 1987, 1990); Bernard and Thomas (1990); Abarbanell (1991); Abarbanell and Bernard (1992); Easterwood and Nutt (1999)].

Few studies, however, investigate the relationship between behavioral tendencies in analysts' earnings forecasts and investors' reactions to such tendencies [Abarbanell and Bernard (1992); Dechow and Sloan (1997); Ackert and Athanassakos (1997)]. This research issue is important because it may enhance our understanding of the persistent post-announcement date stock return anomalies, the validity of model specifications in previous earnings studies, regulatory incentives in securities markets, and investors' rationality in response to analysts' forecasting behavior. In addition, the empirical findings of the current research may improve various asset pricing models, just as other behavioral finance literature has.[4]

A large body of literature documents that analysts' forecasts provide the best proxy for investors' earnings expectations, and tend to outperform the time-series models [Brown and Rozeff (1978); Fried and Givoly (1982); Givoly and Lakonishok (1984); Conroy and Harris (1987); Brown et al. (1987); O'Brien (1988); Kross, Ro, Schroeder (1990)]. The recent studies about systematic behavioral tendencies in analysts' forecasts and investors' expectations utilize analysts' forecast errors based on analysts' forecasts compiled from a variety of sources [Abarbanell and Bernard (1992); Ali, Klein, and Rosenfeld (1992); Elliott, Philbrick, and Wiedman (1995); La Porta (1996); Ackert and Athanassakos (1997); Clement (1999); Easterwood and Nutt (1999)]. In line with these

[4] Traditional asset pricing models (e.g., CAPM and APT) assume market efficiency. These models imply that abnormal returns cannot exist in equilibrium taking necessary factors (e.g., market portfolio returns, interest rates, size effect, and so forth) into consideration. They do not consider investors' quasi-rational behavior as a necessary factor.

studies, the Institutional Brokers Estimate System (*I/B/E/S*) quarterly consensus earnings forecasts are used for this dissertation.

There is a wealth of literature studying stock price reaction to analysts' forecasts errors or revisions [Givoly and Lakonishok (1979a, 1979b); Hughes and Ricks (1987); Cornell and Landsman (1989); Teets (1992); Alexander, Jr. (1992); Abarbanell and Bernard (1992)]. These studies explicitly or implicitly assume that investors' reaction to earnings information is a function of analysts' forecasts, as if investors' earnings expectations equal analysts' forecasts. A common functional form that shows this relationship is:

$$CAR_{it} = f(FE_{it}) \tag{1-1}$$

where

CAR_{it} = the cumulative abnormal return for the event period around the earnings announcement t for firm i (e.g., 1-year holding period, from –2 to 0 relative to the announcement date, or 1-month abnormal return in the month including the announcement date, and so forth.);[5]

FE_{it} = analysts' earnings forecast errors at the earnings announcement t for firm i ($= A_{it} - F_{it}$);

A_{it} = actual earnings at the earnings announcement t for firm i; and

F_{it} = analysts' consensus forecasts for A_{it}.

[5] In this research, CAR_{it} indicates the market-model adjusted 3-day [-2:0] cumulative abnormal returns at the quarterly earnings announcement t for firm i.

Analysts and investors are different types of market participants and may possess different information sets as well as different behavioral characteristics.[6] Analysts' forecasts, then, may not be an appropriate proxy for investors' expectations. For example, suppose analysts' forecasts are biased, but investors can estimate the bias and adjust accordingly. If so, the previous studies about information content of contemporaneous unexpected earnings (i.e., forecast errors) may have provided spurious results.

Because analysts' forecasts may not be the same as investors' earnings expectations, the conclusions of prior research using functional forms similar to Equation (1-1) may involve invalid inferences about the relationship between unexpected earnings information and investors' reaction to it. In short, the empirical framework for displaying the relationship between stock price movement and unexpected earnings information may have been misspecified in prior studies.

To illustrate, first suppose that analysts' forecasts are, indeed, the best proxy for investors' expectations about future earnings. Then, investors' expectations can be expressed as follows:

$$\text{Investors' Expectations } (E_t) = \text{Analysts' Forecasts } (F_t) = f(\theta_t, B_{analyst}) \qquad \text{(1-2)}$$

where

θ_t = information sets of analysts at the quarterly earnings announcement t;

$B_{analyst}$ = analysts' behavioral tendencies at t; and

F_t = analysts' earnings forecasts at t.

For convenience, firm subscripts are dropped hereafter.

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[6] Recall that I use the term "behavior" to indicate non-economic behavior based on the subjective

I refer to the assumption that investors' expectations equal analysts' forecasts as the naïve expectations hypothesis (*NEH*). The conclusions of previous studies that use analysts' forecasts as the proxy for investors' expectations should then be qualified by the *NEH*. The *NEH* predicts that investors naively follow analysts' forecasts when they form their expectations about contemporaneous earnings. Note that naïve reaction is a type of quasi-rational behavior.

There is, however, growing evidence that analysts' forecasts may exhibit systematic patterns, which may be used to classify analysts' behavior (e.g., optimistic, pessimistic, or rational). If investors incorporate their knowledge of such systematic patterns in analysts' forecasts rather than naively accepting the forecasts at face value, then the *NEH* is invalid.

My research postulates that the *NEH* is a questionable approach because investors may adjust for analysts' forecasting behavior, and/or display behavioral tendencies themselves. For example, suppose analysts issue biased forecasts, and investors know the direction of the bias. That is, investors' expectations are conditioned on investors' information sets and the behavioral tendencies of both investors and analysts:[7]

$$\text{Investors' Expectations} = f(\phi_t, B_{Investor}) \qquad (1\text{-}3)$$

where

ϕ_t = information sets of investors, which include knowledge of systematic

probability of a subject.

[7] Although the two information sets intersect, they are assumed to be different because the financial analysts are likely to have information advantages over investors due to analysts' superior expertise and better position for information collection. Investors' information sets may also include knowledge of analysts' behavior. Because of the passage of Regulation FD, the gap between the two may be narrowed.

behavioral tendencies of analysts, $B_{analyst}$, and their recent earnings forecasts; and

$B_{investor}$ = non-economic behavioral tendencies of investors.[8]

If analysts' forecasts and investors' expectations are significantly different, investors' reactions to unexpected earnings information calculated by using analysts' forecasts (i.e., analysts' forecast errors; FEs) may not be viewed as valid indicators of investors' reactions to their own expectation errors. If investors' earnings expectations are not equal to analysts' forecasts, analysts' forecast errors are not the real unexpected earnings information. It is thus necessary to distinguish between investors' expectation errors and analysts' forecast errors.

A more general approach proposed herein decomposes investors' reaction to the earnings announcement based on analysts' forecasts into two components: self-collected information that contains analysts' behavior and forecasts (ϕ_t), and investors' own behavioral tendencies in earnings expectations ($B_{investor}$) as shown in Equation (1-3). The first component can be seen as a combination of analysts' forecasting behavior and residual self-collected information. The *NEH* implies that investors ignore analysts' past forecasting behavior.

On the other hand, investors may rationally take analysts' forecasting behavior into account and adjust for it when they form their own earnings expectations. In this case, analysts' forecasting behavior is a significant determinant of investors'

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[8] Note again that non-economic behavioral tendencies are defined as a type of quasi-rational behavior [Thaler (1986)].

expectations, and investors' reaction to earnings surprises (analysts' forecast errors) is unlikely to reflect systematic underestimation or overestimation. Based on this argument, an alternative hypothesis to the *NEH* is defined as the hypothesis that investors rationally adjust for observed analysts' forecasting behavior, and will be called rational expectations hypothesis (*REH*).[9]

Under the *REH* the market reaction to the earnings announcement for an optimistic stock will be significantly different from that for a pessimistic stock.[10] The rational investors fully adjust for analysts' optimism by discounting analysts' optimistic forecasts or fully account for analysts' pessimism by placing a premium on analysts' pessimistic forecasts. They will not, as a result, take at face value the unexpected earnings information (i.e., analysts' forecast errors) at the earnings announcement.

The *NEH* and the *REH* are not exhaustive hypotheses of investor behavior. The *NEH* demonstrates the most simplistic type of quasi-rational investor behavior (naïve following of analysts' forecasts), while the *REH* presumes fully rational investor behavior (full adjustment of analysts' forecast bias). Alternative hypotheses involve what might be collectively termed variations of quasi-rationality.[11] For example, what if investors amplify or over-adjust for analysts' optimism or pessimism in earnings forecasts? If this is the case, analysts' optimism will be reinforced or overly discounted in the investors' reaction to earnings surprises, while analysts' pessimism will be reinforced or given too

[9] Note that while analysts' earnings forecasts are observable, investors' earnings expectations are not. In this research, investors' earnings expectations can be indirectly inferred by examining the two proposed hypotheses: *NEH* and *REH*.
[10] A(n) pessimistic (optimistic) stock indicates a stock that has been characterized by analysts' pessimism (optimism) in quarterly earnings forecasts.
[11] Consistent with Thaler (1986), the quasi-rational behavior here is defined as behavior that is "purposeful, regular, and yet systematically different from the axioms of economic theory (p. S280).

much premium. That is, investors are neither naïve nor fully rational. Alternative hypotheses vary with investors' behavioral tendencies (other than naïve) in earnings expectations, they might be termed the behavioral expectations hypothesis (BEH) collectively. Although the BEH is an important aspect of research, I will suppress its discussion for the purpose of parsimony.[12]

1.2 Motivations

1.2.1 Need for New Perspective: A Valid Specification

As noted in the previous section, few studies have evaluated investors' reaction to analysts' forecasting behavior. Most existing studies have largely ignored the "behavior" element of analysts' forecasts as a determinant of investors' expectations in future earnings, implicitly assuming that investors take analysts' forecasts at face value. The literature has by-and-large implicitly assumed that investors' reaction to earnings information is characterized by the *NEH*. However, my approach incorporates analysts' forecasting behavior into the model in which investors' reaction to earnings announcements is examined.

If investors' expectations significantly differ from analysts' forecasts, this functional form is misspecified, since investors' reaction is based on additional

[12] If I discuss the BEH along with the *NEH* and the *REH*, I may end up producing many speculations about investors' reaction to analysts' forecasting behavior as opposed to showing economically meaningful empirical findings. I will briefly discuss the BEH in Chapter 7 and give some speculation about the market reaction to analysts' forecasting behavior under the BEH.

information about analysts' forecasting behavior which is known to them, and which may cause investors to view analysts' forecasts as biased. Thus, Equation (1-1) should incorporate investors' expectations (E_t) into the function instead of analysts' forecasts (F_t). The functional form I propose is:

$$CAR_t = g(TE_t) \tag{1-4}$$

where

TE_t = investors' expectation errors = $A_t - E_t$; and

other terms are as defined before.

It is now obvious that the traditional functional form, $CAR_t = f(FE_t)$, should be modified if investors' expectations are believed to be different from analysts' forecasts. If analysts' forecasts (F_t) are not, in fact, unbiased estimates of investors' expectations (E_t), then the parameter estimate of analysts' forecast errors (FE_t) is a biased measure of the market sensitivity to investors' expectation errors to the extent of the systematic difference between E_t and F_t.

Research for the relation between analysts' forecasting behavior and investors' expectations in future earnings remains largely an uncharted area. Such research enables a more thorough investigation on the relevance of earnings information flows from firms to analysts to investors.

The empirical findings would have important implications for investments and regulatory policies. For instance, in this case the naïve investors take analysts' forecasts as unbiased the naïve investors' forecast errors are equal to analysts' forecast errors. By definition, these investors will experience misperceived earnings surprise with the result that the stocks will be mispriced during the announcement period. However, notice that this does not take into account a multi-period view. One interesting research question would be whether and how the mispricing corrects itself, and if so, when it happens.

If it can be shown that the underpricing is systematically associated with analysts' forecasting behavior, regulators may have incentives to ensure that investors have the information necessary to better assess analysts' earnings forecasts. The Securities and Exchange Commission's Regulation FD (Fair Disclosure) became effective on October 23, 2000, and may be a consequence of such incentives.[13]

1.2.2 Defining Optimism and Pessimism as Behaviors

A shortcoming of the extant studies about analysts' forecasts and investors' reaction to the earnings announcement is that, taken collectively, they do not provide readers with clear definitions of such concepts as overreaction, underreaction, optimism, or pessimism.[14] Some studies define overreaction as overweight on current unexpected

[13] "Regulation FD (Fair Disclosure) is a new issuer disclosure rule that addresses selective disclosure. The regulation provides that when an issuer, or person acting on its behalf, discloses material nonpublic information to certain enumerated persons (in general, securities market professionals and holders of the issuer's securities who may well trade on the basis of the information), it must make public disclosure of that information" [Federal Register: August 24, 2000 (Volume 65, Number 165, pp. 51715-51740)]. The Regulation FD was passed on August 10, 2000, appears in Federal Register, and took effect on October 23, 2000.

[14] Unless qualified, overreaction, underreaction, optimism, and pessimism indicate both analysts' and investors' perspectives. For example, optimism implies either analysts' or investors' optimism, while analysts' optimism means only optimistic behavioral tendencies in analysts' forecasts.

earnings information (i.e., analysts' forecast errors) resulting in either overvaluation or undervaluation, and underreaction as underweight on current unexpected earnings information (resulting in either undervaluation or overvaluation).[15] There is, however, no universal agreement among existing studies on how the terms describing behavioral phenomena are defined.

Although optimism and pessimism are the concepts that are closely associated with both underreaction and overreaction, the former have attracted less attention than the latter, and have not been discussed in depth until recently. La Porta (1996) implies that analysts' optimism is equal to the difference between the actual values of earnings and analysts' forecasts where analysts' forecasts are greater than the actual earnings. Thus, he argues that if analysts' forecast errors, $A_t - F_t$, are consistently negative it means analysts are, on average, optimistic. Because most existing studies either explicitly or implicitly assume that analysts' forecasts are an appropriate proxy for investors' expectations (i.e., they assume the *NEH*), the same notions of optimism in analysts' forecasts have been applied to investors' expectations.

Easterwood and Nutt (1999) provide a different definition of analysts' optimism, arguing that in an optimistic framework analysts tend to underreact to negative information and overreact to positive information.[16] As shown in their paper, analysts' optimism is not mutually exclusive of either overreaction or underreaction, but

[15] That is, overweighting positive earnings news results in overvaluation while overweighting negative earnings news leads to undervaluation. Most of existing studies haven't explicitly taken the types of news (i.e., good or bad) into consideration.
[16] From the optimism definition, I can induce the definition of pessimism: overreaction to bad news and underreaction to good news. These definitions of optimism and pessimism are inconsistent with the existing definitions of optimism and pessimism in overreaction and underreaction studies.

interdependent. Analysts’ overreaction to bad news is actually a pessimistic reaction, as is underreaction to good news. On the other hand, analysts’ underreaction to bad news indicates an optimistic behavior, as does overreaction to good news. Certain patterns of over- and underreaction lead to optimism, and other patterns, to pessimism, but clearly the simple over- and underreaction dichotomy is not equivalent to the optimism and pessimism dichotomy. It should, however, be noted that the operational definitions of analysts' optimism and pessimism, whatever the underlying cause, are still negative forecast errors and positive forecast errors, respectively.

1.3 Concluding Remarks

Investors have access to information about prior forecast errors. Therefore, one way of discovering analysts' behavior is to analyze historical data.[17] This is why "persistence", if it exists, is an important empirical trait. If analysts' optimism or pessimism is, indeed, persistent, then another important question arises: How is analysts' optimism or pessimism incorporated into investors' expectations about future earnings? Testing the *NEH* against the *REH* will provide an empirical answer to this question.

I use portfolios of stocks to test the proposed hypotheses, and these portfolios are formed on the basis of the historical record of analysts' forecasting behavior prior to the earnings announcement. To capture analysts' forecasting behavior, the quarterly consensus earnings forecasts and actual earnings compiled from *I/B/E/S* are used. It

[17] Other methods are conceivable, but impractical (e.g., give each analyst a battery of psychological tests just prior to every forecast).

should be noted that tests of the *NEH* versus the *REH* using the formed portfolios are based on the following presumptions:

(a) Historical data can be used to determine the range of analysts' forecasting behavior.

(b) Analysts' forecasting behavior is a significant determinant of investors' earnings expectations.[18]

(c) Investors' behaviors are dichotomized into naïve and rational.

In summary, this research intends to answer the following two questions: 1) Whether the bias in analysts' earnings forecasts is persistent and therefore knowable; 2) If it is indeed, how investors respond to such bias. The empirical findings would improve asset pricing models, suggest better model specifications in related studies, provide regulatory policy implications, and facilitate discussions on investor rationality.

The dissertation is presented in the following order. In the next chapter, the existing literature is reviewed. Chapter 3 sets forth the hypotheses to be tested and addresses the empirical models to test the hypotheses. In Chapter 4, two portfolio formation methods that measure analysts' forecasting behavior are introduced, and 5 portfolios of observations (firm-quarters) revealing the range of such behavior are formed. Chapter 5 introduces the sample and describes the abnormal return measures. Chapter 6 presents and discusses the empirical findings, and also suggests their implications. Chapter 7 summarizes and concludes my dissertation.

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[18] It is implicitly required to have persistent analysts' forecast errors (or bias) over a certain period of time so that investors are really exposed to systematic patterns in analysts' forecasts.

Chapter 2

Literature Review

2.1 Overview

Since the De Bondt and Thaler's seminal work (1985), a great deal of research on inefficiency in analysts forecasts and investors reaction to the earnings announcement has constituted a literature of earnings studies. The existing literature regarding analysts' and/or investors' reaction to earnings information can be divided into three categories: Overreaction and underreaction from investors' perspectives, overreaction and underreaction from analysts' perspectives, and optimism and pessimism from analysts' perspectives.[19] Some studies are supportive of the rational hypothesis that analysts and/or investors fully utilize all available information and produce unbiased expectations about future earnings, while the others support the quasi-rational hypothesis that expectations about future earnings tend to show systematic bias. The latter studies are collectively called behavioral finance. In the following sections major studies in behavioral finance are contrasted with rationality-based literature.

[19] Recall that most existing studies do not investigate analysts' forecast bias and investors' reaction to the earnings announcement sequentially or simultaneously, although they seem highly correlated events. In other words, the existing studies tend to separate investors' earnings reaction behavior from analysts' forecasting behavior. As a result the former type of studies take into consideration investors' point of view

2.2 Overreaction and Underreaction: Investors' Perspectives

Many studies in this category of literature investigate the autocorrelation structure of analysts' forecast errors, the post-earnings-announcement drift, or the mean reversion of stock returns following the earnings announcement. To show the autocorrelation structure in analysts' forecast errors, a handful of studies use distributed-lag models similar to the following regression model [Bernard and Thomas (1990); Mendenhall (1991)]:

$$CAR_t = \gamma_f + \gamma_0 FE_t + \gamma_1 FE_{t-1} + ... + \gamma_k FE_{t-k} + \varepsilon_t \qquad (2\text{-}1)$$

where

γ_f = the intercept term;

γ_k = the earnings response coefficient for the forecast error, FE_{t-k} [k = 0, …, K(=an integer)];

ε_t = a random error term assumed independently and identically distributed; and

other terms are as defined earlier.

Note that by assuming that stock returns are a function of analysts' forecast errors, studies using this type of model implicitly adopt the *NEH*. Some studies use lagged abnormal returns as regressors while others use both lagged forecast errors and abnormal returns, and the number of lags, k, is usually less than or equal to 4. Positive (negative)

(perspective) on the earnings information, seemingly independent of analysts' point of view (perspective) on the same information.

slope coefficients in a declining pattern in absolute values during a forecasting period would indicate systematic underreaction (overreaction) of investors to the earnings announcement.

Another popular technique to investigate investors' underreaction or overreaction is to look at the movements of post-announcement abnormal returns relative to pre-announcement abnormal returns or pre-announcement performance (i.e., portfolios based on pre-announcement stock performance, such as winner and loser portfolios) [Bernard and Thomas (1989); Chan, Jegadeesh, and Lakonishok (1996); La Porta (1996)]. To determine whether abnormal stock returns are permanent or not, post-announcement abnormal returns are plotted against post-announcement time period (e.g., month, quarter, or year).[20] If the abnormal returns show increasing or decreasing patterns in the same (opposite) direction as pre-announcement returns, it is taken as evidence of underreaction (overreaction). Other researchers compare winner and loser portfolios instead of comparing pre- and post-announcement abnormal returns.

2.2.1 Overreaction

De Bondt and Thaler (1985) conclude that investors tend to place too much weight on recent earnings information instead of long-term earnings power, and suggest that corrections of such overreactions explain the long-term reversals of extreme prior stock price changes. They cite behavioral research to support the overreaction hypothesis

[20] The maximum period is usually 5 years.

under which overreaction to recent information characterizes the securities markets. Behavioral researchers such as Kahneman and Tversky (1982) argue that individuals are apt to overreact to unexpected news events, and thus Bayes' rule does not characterize behavior of individuals.

De Bondt and Thaler (1987) reevaluate the behavioral hypothesis of investor overreaction found in their 1985 paper by discussing some unresolved issues (e.g., the effects of size and time-varying risk premia) related to the winner-loser anomaly. They confirm the winner-loser effect they found in their 1985 paper, and in addition they suggest that the size effect and difference in risk are not responsible for the winner-loser effect. They show that risk disparity between the loser and winner portfolios is insufficient to account for the return gap between the two portfolios. For example, for annual returns, the CAPM beta for the loser portfolio in up markets is 1.388 and the beta in down markets is 0.875. On the other hand, the beta for the winner portfolio in up markets is 0.993 and the beta in down market is 1.198. They argue that it is not reasonable to say that a portfolio with betas of 1.388 and 0.875 in up and down markets respectively is riskier than one with betas of 0.993 and 1.198 in up and down markets.[21] Thus, the risk effect is rejected. Furthermore, De Bondt and Thaler find that the small firm effect is not observed in their data.

Chopra, Lakonishok, and Ritter (CLR; 1992) and Lakonishok, Shleifer, and Vishny (LSV; 1994) provide additional evidence of the overreaction effect even after controlling for fundamental risks. CLR use an OLS multiple regression model

[21] De Bondt and Thaler (1987, p. 568)

incorporating both size and risk measured as the portfolio rank, and test the overreaction effect. CLR form 20 portfolios by continuously ranking stocks each year on the basis of their 5-year buy-and-hold returns. Portfolio 1 consists of stocks with the lowest ranking-period returns, and Portfolio 20 consists of stocks with the highest ranking-period returns. They obtain evidence that extreme losers (stocks in Portfolio 1) outperform extreme winners (stocks in Portfolio 20) by 5 percent per year, even after controlling for size, prior returns, and betas. This evidence is much stronger for smaller firms than for larger firms. For example, among small firms the abnormal return spread between extreme losers and winners increases to 10 percent per year. CLR argue that, considering that individuals are predominant shareholders of small firms while institutional investors predominantly hold large firms, this is a reasonable result.

LSV also provide evidence that contrarian strategies yield significant abnormal returns by exploiting the suboptimal behavior of the typical investors. Like many others, LSV form value and glamour portfolios. But, unlike the others, they use four different measures: B/M (book-to-market), C/P (cash flow to market value of equity), E/P (earnings-to-price), and GS (growth rate of sales). LSV contend that value stocks are no riskier than glamour stocks.[22]

La Porta (1996) examines systematic errors in analysts' forecasts, extrapolation, and contrarian strategies, and reports that analysts' forecasts about earnings growth are too extreme and contrarian strategies do earn abnormal returns. Consistent with his

[22] Note that there are also studies against investors' overreaction. For example, Chen and Sauer (1997) reexamine the overreaction hypothesis by testing the contrarian investment strategy and find that the existence of overreaction depends on the sample periods studied. They argue that the contrarian strategy

expectation, the average raw returns of low-growth firms are 20.9 percentage higher than those of high-growth firms. He argues that these results are robust even after controlling for both size and book-to-market ratios, and that a particular time period does not seem to drive the superior performance of low-growth firms. Notice that La Porta implicitly assumes investors' naïve reaction to extreme analysts' forecast about earnings growth.[23]

Rozeff and Zaman (1998) provide another evidence on investor overreaction. They create deciles of stocks based on a ratio of cash flow to market value of equity each year for each firm, and as a result value stocks (i.e., highest-decile stocks) and growth stocks (i.e., lowest-decile stocks) are obtained. Then, Rozeff and Zaman examine the direction of insider trades along the growth/value spectrum, and find that insider buying increases as stocks increasingly become value stocks, and insiders tend to sell the stocks that experienced high returns. This implies that growth stocks are overvalued and value stocks are undervalued by the outside investors. This is consistent with the predictions of the overreaction hypothesis. Seyhun (1990) also investigates insider trades in response to the 1987 Market Crash. To see whether investors reveal their overreacting behavior in the Crash, Seyhun examines the relation between stock returns before and after the Crash, insider trading activity, and pre-Crash market risk in a multiple regression framework. He finds similar results to Rozeff and Zaman (1998). That is, insiders' buying jumps right after the Crash and the stocks bought by insiders experience larger positive returns.

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earns abnormal profits only for specific time periods such as pre-war or pre-energy crisis while the winner-loser portfolio relationship becomes ambiguous during post-war period (i.e., 1940-1950s).

[23] If it turns out that investors are, in fact, somewhat rational, we may not attribute the observed abnormal returns from contrarian strategies to extreme analysts' forecasts in earnings growth.

Testing both the uncertain information hypothesis and the overreaction hypothesis, while controlling for size effect, changes in market volatility, and event direction (positive or negative), Ketcher and Jordan (1994) document short-term market overreaction. They report that positive (negative) events are followed by negative (positive) abnormal returns. Zarowin (1989) also identifies the short-run overreaction effect by examining winner and loser portfolios. Zarowin finds that losers outperform winners in the subsequent month following extreme performance month.

Controlling for risk changes in addition to other influential components such as bid-ask spreads, infrequent trading, and firm size, Dissanaike (1997) reexamines the overreaction hypothesis. He finds supporting evidence for the overreaction hypothesis that contrarian portfolios (winners – losers), in general, earn negative abnormal returns during the periods: 12, 18, 24, 30, 36, 42, and 48 months.[24]

Observing the index futures market in the US and Hong Kong, Fung, Mok, and Lam (2000) investigate whether intraday price reversals occur in this market. Rejecting the effects of bid-ask spread and investor panic at market opening, they show that futures price reversals following large changes in futures price do occur in both the S&P 500 futures and the Hang Seng Index Futures (HSIF) in Hong Kong. Taking contrarian trading strategies considering transaction costs and execution time lag, Fung et al. show that the contrarian strategies are associated with positive abnormal returns with a maximum annual return of 26 percent for the HSIF.

[24] Dissanaike (1997, p. 44-45) also finds some evidence of underreaction when shorter rank periods (24 or 36 months) are used.

2.2.2 Underreaction

In sharp contrast to the overreaction studies, Abarbanell (1991), Abarbanell and Bernard (1992), Elliot, Philbrick, and Wiedman (1995), Lys and Sohn (1990), and Mendenhall (1991) report that investors underreact (underweight) to new information such as interim earnings announcements or changes in stock prices.

Abarbanell and Bernard (1992) confirm the underreaction hypothesis that investors underreact to earnings announcements and the subsequent completion of the reaction results in a post-earnings-announcement drift. Abarbanell and Bernard show that investors appear to underreact to the earnings announcement to an even greater degree than analysts.

Suggesting less noisy measures of the information content of analysts' forecasts called updated measures of earnings information content, Stickel (1991) documents that the market tends to underreact to analysts' forecast revisions. The underreaction results in price drift in the direction of a revision for about six months after the revisions. According to Stickel, forecast revisions influence stock prices, but stock prices do not fully and immediately incorporate the unexpected earnings information. Especially, the market reaction to forecast revisions is greater for the top or bottom 5 percent of the distribution of all forecast revisions, and he finds that the spread between the abnormal returns of confounding revisions (i.e., preceded by earnings, dividend, and stock-split announcements) and those of non-confounding revisions is not significantly different from zero. The abnormal market reaction continues to drift in the direction of the revisions at least for 6 months.

Bernard and Thomas (1989) investigate two competing explanations for post-earnings-announcement drift: delayed price response and risk premium. They examine various forms of CAPM misspecification – misestimation of beta, exclusion of risk factors other than systematic market risk, and taxes – as alternative explanations for post-earnings-announcement drift, but find no evidence that these factors sufficiently explain the post-announcement drift. Instead, Bernard and Thomas argue that a delayed response to earnings information results in the post-announcement drift, and suggest that transaction costs and failure to full recognize the implications of current earnings for future earnings are possible reasons for this phenomenon.

Relating the relative magnitudes of market reactions to the autocorrelation structure of forecast errors, Bernard and Thomas (1990) find a negative relation between forecast errors at quarter *t (or t-4)* and abnormal returns around the quarterly earnings announcement at *t+4 (or t)*, and positive but declining relations between adjacent forecast errors at quarters *t+1, t+2, and t+3 (or t-1, t-2, and t-3)* and abnormal returns around the quarterly announcements for quarter *t+4 (or t)*. The latter relations are consistent with the underreaction effect, and the former relation indicates overemphasis on the earnings of the same quarter of the prior year.

Chan, Jegadeesh, and Lakonishok (1996) investigate both price and earnings momentum strategies across decile portfolios. The decile portfolios are formed by ranking stocks on the basis of either prior six-month returns or a measure of earnings news.[25] They find that both momentum strategies produce economically meaningful price drift that lasts for at least 6 months. For example, portfolios formed by prior six-month returns of stocks yield mean return spreads of 8.8 percent over the following six months while those sorted by a moving average of past consensus forecast revisions create mean return spreads of 7.7 percent over the subsequent six months.[26]

2.2.3 Evidence of Rationality

In this section, I contrast the overreaction studies with the underreaction ones. The main presumption of both types of studies is that investors are not perfectly rational, rather they are quasi-rational. Recall that "quasi-rational" market participants including investors are defined as the ones who possess behavioral tendencies in reaction to stock price information. For instance, "naïve" investors mean the ones who naively take analysts' earnings forecasts as unbiased even when they can observe that analysts' forecasts are persistently biased. Thus, the naïve reaction of investors to such bias is a type of quasi-rational behavior [Thaler (1986)].

There is also, however, a large amount of research that is consistent with the rational hypothesis – i.e., investors behave on the basis of economic incentives (i.e., rational as opposed to quasi-rational). Among others, Chan (1988), Ball and Kothari

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[25] A stock's past compound return is used as the ranking variable for the price momentum strategy, while three measures of earnings news [standardized unexpected earnings (SUE), the cumulative abnormal returns around the earnings announcement, and analysts' forecast revisions] are used as the ranking variable for the earnings momentum strategy.

[26] Comparing price drift of dividend initiation with dividend omission, Michaely, Thaler, and Womack (1995) document significant price drifts for both initiation and omission announcements over the next three years.

(1989), and Akhigbe, Gosnell, and Harikumar (1998) report findings in favor of the rational hypothesis.

Chan (1988) and Ball and Kothari (1989) contend that variation in risks plays a main role to induce losers' outperformance and negative autocorrelation in returns. Chan finds that the contrarian strategy yields only small abnormal returns for losers after controlling for risk changes. Ball and Kothari come to a similar conclusion. They suggest that negative serial correlation is attributed almost entirely to changes in relative risks. These results are sharply inconsistent with the overreaction hypothesis. Akhigbe, Gosnell, and Harikumar (1998) test for market efficiency controlling for bid-ask spread, and report weak winner-loser effect (i.e., a contrarian strategy fails to exploit significant abnormal returns).

2.2.4 Summary

The findings on the issue of investors' over- and underreaction are mixed. The point, however, is that few studies make clear how investors perceive and react to analysts' forecasts about future earnings. For instance, it is barely known whether analysts' forecast bias is persistent, how investors respond to the persistent bias in analysts' earnings forecasts, and what factors make investors overreact or underreact to earnings information. This dissertation provides direct suggestions for the first two questions and indirect implications for the third.

2.3 Overreaction and Underreaction: Analysts' Perspectives

2.3.1 Overreaction

In 1990, De Bondt and Thaler find that analysts systematically overreact to new earnings information. They estimate a simple linear model that regresses actual changes in earnings per share (EPS) on forecasted changes in EPS. They observe a negative constant term and a positive slope coefficient less than one. The negative constant term indicates that analysts' forecasts are optimistic (i.e., analysts' forecasts in EPS should exceed the actual EPS to offset the negative constant). The positive slope less than one suggests that actual earnings change by less than the change in analysts' forecasts. For example, from their first model a slope coefficient of 0.648 is estimated. This means that actual earnings change (AEC_t), on average, account for only 64.8 percent of forecasted earnings forecast (FEC_t). They also contend that the market-to-book value (MV/BV) and the past growth rate of earnings are significantly associated with analysts' forecast errors. That is, high MV/BV and high past earnings growth rate are significantly related to optimism, and low MV/BV and low growth rate leads to pessimism.[27]

La Porta (1996) tests how analysts revise the expected rates of low-growth and high-growth stocks from year *t to t+1*, and documents that the expected rate of low-

[27] Also, there are studies in contrast to the overreaction hypothesis for analysts. For instance, testing a linear model regressing contemporaneous forecast errors on prior change in actual earnings, Hussain (1996) provides evidence against the overreaction effect. For the regression model, a negative (positive) slope coefficient indicates that analysts overreact (underreact) to the previous change in earnings. Except for large firms, the slope coefficients are not significantly different from zero, and this suggests that there is no

growth stocks is revised upward from 3.1 percent to 4.1 percent while that of high-growth stocks fall from 21.7 percent to 18.4 percent. That is, there occurs a mean reversion of analysts' earnings growth forecasts – an indication of analysts' overreaction to new earnings information.

2.3.2 Underreaction

Mendenhall (1991) examines the relationship between consecutive earnings forecast errors to test a hypothesis that consecutive forecast errors of analysts are positively associated if analysts underweight the current unexpected earnings information, and supports the hypothesis. Investigating the information content of analysts' forecast revisions, Lys and Sohn (1990) report analysts' underestimation of new earnings information between consecutive forecasts. In other words, analysts do not fully capture new earnings information that becomes available to investors between consecutive forecasts. Abarbanell (1991) conducts similar research. By employing a randomization test on signed analysts' forecast revisions (errors) and signed prior returns, Abarbanell documents a positive relation between analysts' forecast revisions and prior returns as do Lys and Sohn (1990).[28] This indicates that analysts fail to fully incorporate

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evidence of analysts' overreaction. Even in case of large firms, the overreaction effect is diminished after removing influential observations.

[28] The randomization test rejects the null hypothesis of independence between the signs of analysts' forecast revisions and the signs of prior returns, and between the signs of analysts' forecast errors and prior returns. Note that forecast errors are measured by subtracting actual earnings from analysts' forecasts (different from usual calculation). Two return measures are used: raw returns and cumulative abnormal returns (*CARs*). Raw returns are the average daily returns for a firm between earnings forecasts while *CARs* are cumulative abnormal returns (daily) divided by the number of days between forecasts.

prior price changes, and implies that analysts underweight new information. In other words, analysts do not collect and interpret publicly available signals efficiently.

Using the same autoregressive model of analysts' forecast errors as Mendenhall's (1991), Abarbanell and Bernard (1992) document the similar results that Mendenhall reports. Abarbanell and Bernard examine autocorrelations in Value Line analysts' forecast errors, and report positive and monotonically declining autocorrelations at lags 1, 2, and 3 for firm-specific estimates. But, they find no strong evidence of a significant negative autocorrelation at lag 4 indicating that analysts' forecasts do not seem to follow the seasonal random walk model. Such findings are consistent with the underreaction hypothesis that analysts underreact (underweight) to recent earnings information.

Applying Hogarth and Einhorn's (1992) belief-adjustment model to analyst forecasting framework, Elliot, Philbrick, and Wiedman (1995) examine whether analysts' revisions are, on average, sufficient to reflect unexpected earnings information, and document that consensus forecast revisions of analysts tend to underweight unexpected earnings information. They attribute their findings to analysts' conservatism in forecast revisions where individuals make adjustments based Bayesian expectation, but these adjustments are insufficient in amount.

Testing serial correlation and bias in analysts' forecast errors, Ali, Klein, and Rosenfeld (1992) report similar results to Elliot, Philbrick, and Wiedman's. Regressing the current forecast error on the past (one-period back) forecast error and the past stock return, they find significant positive relations between the current forecast error and the past forecast error, and between the current forecast error and the past stock return. The latter results are also found by Beaver et al (1979). This indicates that analysts do not fully incorporate the last year's earnings information and stock returns when they form expectations of future earnings. They extend their research by adding a dummy variable for the persistence of previous earnings (proxied by E/P ratios) and a dummy variable for the previous negative earnings, and find that the tendency to omit the earnings information is greater for firms with permanent earnings than for firms with temporary (mean-reverting) earnings. Ali, Klein, and Rosenfeld affirm that their findings in annual forecasting framework are also observed in monthly forecasting framework.

2.3.3 Summary

This category of research focuses on the relation between contemporaneous and previous analysts' earnings forecast errors, or the relation between actual earnings changes (AEC_t) and forecasted earnings changes (FEC_t) to investigate analysts' behavioral tendencies in earnings forecasts. AEC_t is defined as $A_t - A_{t-1}$, and FEC_t is defined as $F_t - F_{t-1}$, where A_t (A_{t-1}) is actual earnings at time *t (t-1)* and F_t (F_{t-1}) is analysts' forecasts for actual earnings at time *t (t-1)*. General models for analysis are as follows:

$$FE_t = \rho_0 + \rho_1 FE_{t-1} + \rho_2 FE_{t-2} + ... + \rho_k FE_{t-k} + e_t \quad (2\text{-}2)$$

$$AEC_t = \delta_0 + \delta_1 FEC_t + e'_t \quad (2\text{-}3)$$

where all terms are as previously defined.

In Equation (2-2), k is usually less than or equal to four. If the slope coefficients in the equation are positive in declining pattern, then the underreaction hypothesis holds. If they are negative, the overreaction hypothesis holds. For Equation (2-3), the standard definition of unbiased forecasts would require that δ_0 =0 and δ_1=1 [De Bondt and Thaler (1990)]. If forecasted earnings changes ($FECs$) are extreme, then δ_1 will be less than one. In addition, the intercept, δ_0 , is an indicator of bias in the forecast. If analysts' forecasts were upward (downward) biased, δ_0 would be negative (positive).

As in Section 2.2, the studies about analysts' underreaction and overreaction have documented mixed and controversial findings. This implies that neither underreaction nor overreaction is a representative behavioral phenomenon in analysts' earnings forecasts. These results provide evidence that analysts' forecasting behavior may be classified in spectrum so that I can form portfolios with salient features of their forecasting behavior. Note that I later use the terms, optimism and pessimism, rather than overreaction and underreaction because I suspect that the former better capture the range of analysts' forecasting behavior and overreaction and underreaction are not mutually exclusive [Easterwood and Nutt (1999)].

2.4 Optimism and Pessimism: Analysts' Perspectives

Another stream of research on earnings forecasts focuses on optimism and pessimism in analysts' forecasts. This category of study has not been investigated in depth until recently. Many underreaction and overreaction studies incorporate the concepts of optimism and pessimism into underreaction and overreaction discussions [Abarbanell (1991); Francis and Philbrick (1993); La Porta (1996); Dissanaike (1997)]. In such studies, optimism and pessimism are mechanically defined as negative forecast errors (i.e., $A_t - F_t < 0$) and as positive forecast errors, respectively.

Abarbanell (1991) reports that the mean of analysts' forecast errors from 1981 to 1984 is positive (0.04) and the number of overestimated (positive; optimistic) forecast errors exceeds the number of underestimated ones in each of the four years.[29] La Porta (1996) also reports that the actual earnings tend to be lower than corresponding analysts' forecasts for almost all portfolios formed on the basis of growth forecasts – i.e., analysts' forecast errors ($A_t - F_t$) are negative for most portfolios.

Some studies in this category investigate an association between analysts' optimism and such factors as forecasting accuracy, uncertainty, and stock recommendations [Ackert and Athanassakos (1997); Butler and Lang (1991)]. Ackert and Athanassakos (1997) look at the role of uncertainty in analysts' optimism and document that a strong positive relationship between optimism and uncertainty exists. The more uncertain firms are, the more optimistic analysts are. Butler and Lang (1991) study individual analysts' behavior and find that analysts are persistently optimistic or pessimistic relative to consensus forecasts. They report that analysts' average optimism (pessimism) is associated with lower (higher) average forecast accuracy.

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[29] Note that forecast errors here are calculated by subtracting actual earnings from analysts' forecasts: $F_{it} - A_{it}$. Abarbanell contends that deflating forecast errors by stock price does not make qualitative differences in the results he finds. Notice that his forecast error measure is inconsistent with the definition of forecast errors throughout this dissertation: $A_{it} - F_{it}$.

Little research has been done on analysts’ pessimism probably because pessimism is not acknowledged to be underlying feature of analysts' earnings forecasts [Brown (1996)]. By looking at the percentage of positive, negative, and zero forecast errors per quarter from 1991 to 1995, Brown (1996) reports evidence that 12 of 18 quarters considered have higher percentage of positive forecast errors (i.e., actual earnings are greater than *I/B/E/S* analysts’ forecasts) than that of negative forecast errors. He interprets this as a pessimistic tendency of analysts during the period.

Easterwood and Nutt (1999) examine systematic optimism in analysts’ forecasts by incorporating types of news, and by making an effort to link overreaction and underreaction concepts to optimism. Simultaneously investigating overreaction and underreaction in analysts’ forecasts, they reject the overreaction and underreaction hypotheses and document that analysts underreact to negative information (bad news) and overreact to positive information (good news). This implies that there exists systematic optimism in analysts’ forecasts.

2.5 Chapter Summary

Both the overreaction hypothesis and the underreaction hypothesis have contributed to development of research on behavior of analysts and investors. Although they seem to argue against each other, they also seem to coexist. Although Michaely, Thaler, and Womack (1995) provide additional evidence for the underreaction effect, they also acknowledge that “the market appears to overreact in some circumstances and to underreact in others (p. 606)”.[30]

Although analysts' earnings forecasts and investors' expectations about future earnings are not mutually independent issues, few studies have tried to integrate them. Rather, the existing studies investigate such issues as if they are de facto independent. This study is therefore warranted in order to bridge the gap in existing studies.

The findings in the literature are mixed. The contradictions can be attributed to different methodologies, samples, periods, measurements, assumptions, specifications, and so forth. For instance, the results from using Value Line analysts’ forecasts may differ those from employing *I/B/E/S* forecasts; assuming that investors naively follow analysts’ forecasts at face value may be inappropriate; results may be attributed mainly to additional risk factors such as firm size and/or market-to-book ratio, not to overreaction or underreaction; it may be that the overreaction effect is a phenomenon for pre-war periods or for the expansion periods; the error terms of OLS models may not satisfy the traditional assumptions; necessary explanatory variables are omitted. Taking these possibilities into consideration is worthwhile, since it surely improves the validity and reliability of research. Therefore, it is important for a researcher to keep these in mind when performing an empirical study regarding analysts’ forecasting behavior and investors' expectations about future earnings.

It should be noted again that most existing literature implicitly assumes investors naively follow analysts' forecasts – *NEH*. The *NEH* is questionable given the fact that

[30] Also see Fama (1998).

investors can observe the historical record of analysts' forecasting behavior, since they might fully adjust for such behavior if they are rational.

Chapter 3

Hypotheses Development and Empirical Models

3.1 Hypotheses Development

As discussed in the previous chapters, investors' reaction to analysts' forecasting behavior has not been a theme.[31] In this dissertation, I endeavor to fill a gap by examining analysts' forecasting behavior from investors' perspectives. This is a new approach because extant studies have not placed much emphasis on the formation of investors' expectations in response to analysts' forecasting behavior in earnings forecasts. In the following discussion, I will develop testable hypotheses – the naïve expectations hypothesis (*NEH*) and the rational expectations hypothesis (*REH*) – along with qualifications.

As introduced earlier, for previous studies about investors' reaction to the earnings announcement a common functional form is:[32]

$$CAR_t = f(FE_t) = \alpha' + \beta' FE_t + \varepsilon_t' , \qquad (3\text{-}1)$$

where all terms are as defined earlier.

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[31] Notice that I here use the term "forecasting behavior" instead of "forecast bias." I use "forecasting behavior" to emphasize that analysts' forecast bias is persistent. That is, I implicitly assume that analysts persistently issue biased forecasts in either optimistic or pessimistic direction. Recall that whether analysts' forecast bias is persistent is one of the two main research questions to be addressed in my dissertation. I perform a few persistence tests on analysts' forecast bias in Chapter 6, since the persistent bias in analysts' earnings forecasts is a necessary condition for testing the *NEH* versus the *REH*.
[32] Note again that firm subscripts are suppressed.

Also, recall that due to the potential persistent bias in analysts' forecasts I develop a modified functional form incorporating investors' expectations:

$$CAR_t = g(TE_t) = \alpha'' + \beta'' TE_t + \varepsilon_t'' \tag{3-2}$$

where all variables are as previously defined.

Recall that most research studying the market reaction to the earnings announcement assumes that analysts' forecasts are not biased – i.e., takes the *NEH* for granted. Equation (3-2), however, suggests that the earnings response coefficient (β') in Equation (3-1) may not measure the real information content of the earnings announcement (i.e., rational investors' expectation errors) when analysts tend to issue biased earnings forecasts, and that β' may be different from β''. Recall that TE_t represents investors' expectation errors and is equivalent to the difference between actual earnings and investors' expectations (i.e., $A_t - E_t$).[33]

The *NEH* predicts that investors take biased analysts' forecasts at face value and the naïve investors' earnings expectations are equal to analysts' forecasts: $E_t|_{NEH} = F_t$. Investors' expectation errors are, as a result, the same as analysts' forecast errors: $A_t - E_t|_{NEH} = A_t - F_t = FE_t$.

Therefore, under the *NEH* Equations (3-1) and (3-2) are equivalent. In other words, investors' reaction to the earnings announcement given analysts' optimistic behavior is equivalent with that given analysts' pessimistic behavior:

$$CAR_t|_{NEH}^{OPT} = f(FE_t) = CAR_t|_{NEH}^{PESS} = CAR_t|_{NEH}$$

[33] E_t is ex ante investors' earnings expectations. E_t can be either rational or naïve investors' earnings expectations. A_t is ex post actual earnings.

where

$CAR_t |_{NEH}^{OPT}$ = the naïve investors' reaction to analysts' optimism in earnings forecasts manifested in the 3-day [−2:0] CAR; and

$CAR_t |_{NEH}^{PESS}$ = the naïve investors' reaction to analysts' pessimism in earnings forecasts manifested in the 3-day [−2:0] CAR.[34]

On the other hand, rational investors, as opposed to naïve investors, would expect that analysts' forecasts (F_t) exceed the actual earnings (A_t) when they believe that analysts are optimistic. Thus, when rational investors form their own earnings expectations, they discount analysts' optimistic forecasts and their expectations ($E_t |_{REH}^{OPT}$) are ex ante smaller than analysts' forecasts (F_t) or naïve investors' earnings expectations ($E_t |_{NEH}$): $E_t |_{REH}^{OPT} < F_t = E_t |_{NEH}$.[35] It follows that for given actual earnings, rational investors' expectation errors ($A_t - E_t |_{REH}^{OPT}$) are algebraically larger than analysts' forecast errors ($A_t - F_t$) or naïve investors' expectation errors ($A_t - E_t |_{NEH}$): $A_t - E_t |_{REH}^{OPT} > A_t - F_t = A_t - E_t |_{NEH}$ [Figure 1-(a)].[36] Hence, rational investors' reaction to a given analysts' forecast error ($CAR_t |_{REH}^{OPT}$) is algebraically larger than naïve investors' reaction to the same forecast error ($CAR_t |_{NEH}$) as in Figure 1-(b).

[34] In chapter 4, I discuss two portfolio formation methods that describe the range of analysts' forecast bias (or forecasting behavior) based on the 5-year period prior to the earnings announcements. The portfolios ex post consist of three optimistic and two pessimistic ones.

[35] Note that E_{REH}^{OPT} indicates rational investors' earnings expectations given analysts' optimism in earnings forecasts, while E_{REH}^{PESS} means rational investors' earnings expectations given analysts' pessimism. Also note that these expectations are unobservable and can be indirectly inferred by testing the proposed hypotheses.

[36] Figure 1 is located in the Appendix.

The same argument may be applied to the case of analysts' pessimism. The rational investors, who have classified certain analysts as pessimistic, know that analysts' forecasts have been underestimated. Given persistence in analysts' forecasting behavior, investors accordingly expect that the contemporaneous analysts' forecasts display analysts' pessimism in earnings forecasts (i.e., positive FEs). It is, then, predicted that rational investors' earnings expectations in reaction to analysts' pessimism ($E_t|_{REH}^{PESS}$) are algebraically larger than analysts' forecasts (F_t) or naïve investors' earnings expectations ($E_t|_{NEH}$): $E_t|_{REH}^{PESS} > F_t = E_t|_{NEH}$. This results in rational investors' expectation errors given analyst's pessimism ($A_t - E_t|_{REH}^{PESS}$) algebraically smaller than analysts' forecast errors ($A_t - F_t$) or naïve investors' expectation errors ($A_t - E_t|_{NEH}$): $A_t - E_t|_{REH}^{PESS} <$ $A_t - F_t = A_t - E_t|_{NEH}$.

For a given forecast error, provided that $A_t - E_t|_{REH}^{OPT} > A_t - F_t = A_t - E_t|_{NEH}$ in case of analysts' optimism in earnings forecasts and $A_t - E_t|_{REH}^{PESS} < A_t - F_t = A_t - E_t|_{NEH}$ in case of analysts' pessimism, $A_t - E_t|_{REH}^{OPT}$ should be algebraically larger than $A_t - E_t|_{REH}^{PESS}$. In consequence, the market reaction to any given analysts' forecast error conditional on persistent analysts' optimism should be algebraically larger than that conditional on analysts' pessimism: $CAR_t|_{REH}^{OPT} > CAR_t|_{NEH} > CAR_t|_{REH}^{PESS}$.

Notice that I do not discuss investors' earnings expectations and reaction to the earnings announcement conditional on analysts' rational forecasts (i.e., no bias) – ones that show neither analysts' optimism nor pessimism.[37] Given analysts' unbiased (rational) forecasts, both naïve and rational investors' expectations ($E_t|_{NEH}^{RAT}$ and $E_t|_{REH}^{RAT}$) about contemporaneous earnings are predicted to equal analysts' earnings forecasts: $E_t|_{NEH}^{RAT} = E_t|_{REH}^{RAT} = F_t$. Consequently, investigating investors' reaction to analysts' rational behavior is not useful to test the *NEH* against the *REH* because the reaction would be the same under both the *NEH* and the *REH* [Table 1].[38] Since the objective of the dissertation is to investigate how investors respond to persistent bias in analysts' forecasts, I do not endeavor to scrutinize investors' reaction to analysts' rational behavior.

In sum, for any given analysts' forecast error $A_t - F_t$ (FE_t), the rational market reaction should be algebraically smaller (larger) in response to analysts' pessimism (optimism) in earnings forecasts than in response to analysts' optimism. The naïve market reaction to a given forecast error, otherwise, should be the same whatever analysts' forecasting behavior is preceded.

The above discussions lead to the following testable null hypothesis – *NEH*:

NEH: *If investors take analysts' persistent forecast bias at face value, there should be neither a discount for the optimistic bias nor a premium for the pessimistic bias. Specifically, investors' reaction to the earnings announcement is equivalent across the*

[37] Note again that in Chapter 4 I ex post form 5 portfolios consisting of the most optimistic to the most pessimistic portfolios in order.

[38] All tables are located in the Appendix.

range of analysts' forecasting behavior − from optimism to pessimism. This can be summarized as follows: $CAR_t\,|_{NEH}^{OPT} = f(FE_t) = CAR_t\,|_{NEH}^{PESS} = CAR_t\,|_{NEH}$.[39]

One alternative hypothesis to the *NEH* is the rational expectations hypothesis (*REH*). If investors fully adjust for the analysts' persistent bias in earnings forecasts, there should be information premiums for the case of analysts' optimism and information discounts for the case of analysts' pessimism because $A_t - E_t\,|_{REH}^{OPT} > A_t - F_t >$ $A_t - E_t\,|_{REH}^{PESS}$. In other words, for any given forecast error the rational investors' reaction to analysts' optimistic behavior is expected to be algebraically larger than their reaction to analysts' pessimistic behavior: $CAR_t\,|_{REH}^{OPT} > CAR_t\,|_{NEH} > CAR_t\,|_{REH}^{PESS}$.[40]

3.2 Empirical Models

The empirical test of the *NEH* against the *REH* exhibits the range of investors' reaction to analysts' forecasting behavior. As discussed in the following chapter, to implement the empirical test I classify firm-quarter observations into one of the quintile portfolios, ranging from the most optimistic [Portfolio 1 (P1)] to the most pessimistic [Portfolio 5 (P5)]. Investors' reaction to idiosyncratic analysts' forecasting behavior is, then, investigated in three versions of multiple regression models:

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[39] By using the right hand side of Equation (3-1), this equality can be restated as follows: $\alpha^{OPT} + \beta^{OPT} FE_t = \alpha^{PESS} + \beta^{PESS} FE_t$ where α^{OPT} and α^{PESS} are intercept terms and β^{OPT} and β^{PESS} are the slope coefficients for the optimism and the pessimism cases respectively.

[40] Similar to footnote 39, this inequality can be expressed as follows: $\alpha^{OPT} + \beta^{OPT} FE_t >$ $\alpha^{PESS} + \beta^{PESS} FE_t$ where terms are as defined earlier.

$$CAR_t = \alpha_1 P_1 + \alpha_2 P_2 + \alpha_3 P_3 + \alpha_4 P_4 + \alpha_5 P_5 + \beta_1 diffSize_t + \beta_2 diffBtoM_t + u_t \tag{3-3}$$

$$CAR_t = a_1 P_1 + a_2 P_2 + a_3 P_3 + a_4 P_4 + a_5 P_5 + b_1 \frac{FE_t}{STD_t}$$

$$+ b_2 diffSize_t + b_3 diffBtoM_t + \upsilon_t \tag{3-4}$$

$$CAR_t = a_1' + a_2' P_2 + a_3' P_3 + a_4' P_4 + a_5' P_5 + b_1' \frac{FE_t}{STD} + b_2' \frac{FE_t}{STD} P_2 + b_3' \frac{FE_t}{STD} P_3$$

$$+ b_4' \frac{FE_t}{STD_t} P_4 + b_5' \frac{FE_t}{STD_t} P_5 + b_6' diffSize_t + b_7' diffBtoM_t + \omega_t \tag{3-5}$$

where

CAR_t = the 3-day [−2: 0] abnormal stock returns for a quarterly earnings announcement

P_p = a dummy variable that equals one if an observation belongs to portfolio p and zero otherwise, $p = 1, \ldots, 5$;

FE_t = analysts' earnings forecast errors at quarter t, $FE_t = A_t - F_t$, where A_t is the actual quarterly earnings at quarter t and F_t is the most recent analysts' consensus forecasts for A_t;

STD_t = the standard deviation of analysts' consensus forecasts at quarter t;[41]

MVE_t = $P_t \times Shr_t$ where P_t is the closing stock price at the third month of quarter t and Shr_t is the number of common shares used to calculate

[41] Abarbanell and Bernard (1992) use stock price ten days prior to forecast date to deflate forecast errors. In this way, the stock price is unlikely to reflect the information effects of forecasts and earnings announcements. Instead of following this convention, I use the standard deviation of analysts' consensus forecasts as the forecast error deflator to adjust for forecast volatility, which seems to affect *CARs* [Panels C and F of Table 3].

earnings per share (EPS) at quarter t;

$diffSize_t$ = the difference between $\log(MVE_t)$ and the grand mean of $\log(MVE_t)$ where $\log(MVE_t)$ is the logarithm of MVE_t;

$diffBtoM_t$ = the difference between $BtoM_t$ and the grand mean of $BtoM_t$ where $BtoM_t = \dfrac{BVE_t}{MVE_t}$ and BVE_t = common equity (total) at quarter t; and

$u_t, \upsilon_t, \omega_t$ = identically and independently distributed random error terms.

Note that P_t, Shr_t, and BVE_t are extracted from *COMPUSTAT* and firm subscripts are omitted. Also note that I use $diffSize_t$ and $diffBtoM_t$ instead of the logarithm of MVE_t and $BtoM_t$ to adjust for size and book-to-market effects. Notice that average $diffSize_t$ and $diffBtoM_t$ are zero. The portfolio dummies and slopes in each model indicate average fixed and marginal market impacts of the quarterly earnings announcement for each portfolio given average firm size and book-to-market equal zero. This transformation allows direct comparison of the fixed and/or marginal market effects of a portfolio with those of another so that the *NEH* can be tested against the *REH* within each model.

All models perform the market reaction comparisons among portfolios in different empirical formats. In Equation (3-3), the average forecast error (*AFE*) for each portfolio is reflected in the coefficients of P_ps that measure average total market effects of portfolios as if they are fixed, controlling for the size and the book-to-market effects.

Since the forecast error term is not included as an explanatory variable, the magnitudes of $\alpha_1, \ldots, \alpha_5$ will reflect different mean forecast errors for respective portfolios.

Equation (3-4) distinguishes the marginal (slope) market effects from the fixed (intercept) market effects across portfolios, assuming the marginal effects are constant across portfolios. Equation (3-5) relaxes this assumption by permitting the marginal effects to vary across portfolios.[42]

Table 1 summarizes the relationships between analysts' earnings forecasts and investors' earnings expectations and *CARs* for the optimistic portfolios (e.g., P1) and *CARs* for the pessimistic portfolios (e.g., P5) under either the *NEH* or the *REH*.[43] Under the *NEH*, investors' reaction to their own expectation errors (i.e., TE_t) is the same as that to analysts' forecast errors (i.e., FE_t) across portfolios, since naïve investors' earnings expectations are equal to analysts' earnings forecasts: $CAR_t\,|_{NEH}^{OPT} = f(FE_t) = CAR_t\,|_{NEH}^{PESS} = CAR_t\,|_{NEH}$. Specifically, the coefficients of the portfolio dummy variables in Equations (3-3), (3-4), and (3-5) as well as the portfolio slopes in Equation (3-5) are predicted to be statistically the same.

As discussed earlier, the *REH* proposes that at any given forecast errors *CARs* for the optimistic portfolios should be greater than those for the pessimistic portfolios: $CAR_t\,|_{REH}^{OPT} > CAR_t\,|_{NEH} > CAR_t\,|_{REH}^{PESS}$. Specifically, the coefficients (slope and/or

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[42] Note that Equations (3-3) and (3-4) do not include the intercept term to make pair-wise comparisons easy, while Equation (3-5) includes the intercept term using the most optimistic portfolio (P1) as the reference group. Main results are not affected by the choice of either intercept or no-intercept models.

[43] Recall that I do not try to form a rational portfolio because it does not test the *NEH* versus the *REH* in my empirical framework – i.e., for the rational portfolio, if formed, there is no informational distinction between rational expectation errors under the *NEH* and those under the *REH*.

intercept) for the optimism case are predicted to be larger than those for the pessimism. The same argument should hold between the more optimistic and the less optimistic portfolios and between the less pessimistic and the more pessimistic portfolios.

Chapter 4

Portfolio Selection

4.1 Overview

Since investors' perception of the bias in analysts' consensus forecasts is not directly observable, I must estimate the direction and degree of bias that investors impute to a given forecast. I do this by using historical data to create portfolios, which are likely to differ systematically in terms of perceived bias.

To classify observations (firm-quarters) into the portfolios based on analysts' past forecasting behavior, I use two portfolio formation methods: Mean-Frequency Forecast Error (*MFFE*) and Mean-Frequency Time-Series (*MFTS*).[44] The *MFFE* method considers both the mean and frequency of negative analysts' forecast errors (*FEs*).[45] The *MFTS* method extends the *MFFE* by adding time-series characteristics of analysts' earnings forecasts to the *MFFE* and utilizes a time-series regression model developed by De Bondt and Thaler (DBT, 1990). Note that the *MFTS* can reduce the likelihood of incorrectly assigning an observation to a portfolio (i.e., Type II error) at the expense of the sample

[44] A firm-quarter has information about variables of interest (e.g., analysts' forecasts, actual earnings, the market value of equity, the book value of equity, etc.) for a firm at the quarterly earnings announcement. Recall that the term "forecasting behavior" is used instead of "forecast bias" to emphasize analysts' forecast bias is persistent.

[45] The forecast errors (FEs) are defined as follows: $FE_t = (A_t - F_t)$ where A_t = actual earnings at announcement t and F_t = analysts' forecasts for the time t. In the literature, FEs are usually standardized by the stock price prior to the earnings announcement: $SFE_t = FE_t/P_{t-1}$. where SFE_t = standardized forecast error and P_{t-1} = stock price one period (herein, it is 10 days) prior to the quarterly earnings announcement.

size.[46] Serious Type II error may invalidate the test results from the *MFFE*, while Type I error (i.e., the error of falsely excluding an observation from a portfolio when the observation in fact belongs to the portfolio) does not.

Both methods use 5 years of analysts' quarterly earnings forecasts and actual earnings prior to the contemporaneous earnings announcement to get necessary statistics: mean and frequency of negative *FEs*, and the parameter estimates of the *DBT* model. The first two are used to form quintile portfolios for the *MFFE*, while all three statistics are employed for the *MFTS* method. Each portfolio is supposed to represent a different degree of analysts' optimism or pessimism in earnings forecasts.

It should be noted that the portfolio formation methods are built on the premise that analysts' forecasting behavior is persistent and thus historical performance allows meaningful inferences about current analysts' behavior. Given that the test of the *NEH* versus the *REH* is most powerful when comparing extreme portfolios because they more likely contain observations that reflect real optimism or pessimism of analysts relative to in-between portfolios, the hypothesis test using the *MFTS* method and the extreme portfolios would provide an effective robustness test by alleviating Type II error.

Since the validity of the classification methods is critical for the meaningful empirical analysis, I carefully develop the portfolio formation methods. Sections 4.1 and 4.2 demonstrate the *MFFE* and the *MFTS* methods respectively.

[46] Due to an additional restriction employed, the sample size for the *MFTS* is reduced to ¼ level of that for the *MFFE*.

4.2 Mean-Frequency Forecast Error (MFFE) Method

The forecast errors used for the *MFFE* method are consistent with the definitions of analysts' optimism and pessimism made in Chapter 1.[47] That is, if analysts tend to be optimistic (e.g., overreact to good news and underreact to bad news) over the past 5 years, then their mean forecasts are, on average, more likely to be algebraically larger than the mean of actual earnings. It would be also reasonable to predict that the number of negative forecast errors will exceed the number of positive forecast errors.

Similarly, analysts' pessimism is reflected in higher mean forecast errors and higher percentage of positive forecast errors. In sum, the higher mean and frequency of negative forecast errors indicate the higher tendency of analysts toward optimistic forecasts, and vice versa. The following two sections describe the step-by-step process of the *MFFE* method.

4.2.1 Mean Quarterly Forecast Error (MQFE) and Frequency of Negative Forecast Errors

The mean-frequency forecast error (*MFFE*) method is the main portfolio formation method used to classify observations (firm-quarters) into quintile portfolios indicating a spectrum of analysts' forecasting behavior. The first step of the mean-

[47] Recall that negative forecast errors represent optimistic forecasts, while positive forecast errors indicate pessimistic forecasts.

frequency method is to calculate the mean of quarterly earnings forecast errors over the past 20 quarters prior to the earnings announcement. At each quarterly earnings announcement, I look back 20 calendar quarters and calculate the mean quarterly forecast error ($MQFE_{t,20}$):

$$MQFE_{t,20} = \frac{1}{20} \sum_{q=1}^{20} \frac{A_{t-q} - F_{t-q}}{P_{t-q-1}}, \qquad (4\text{-}1)$$

where

q = 1 through 20 quarters prior to the quarterly announcement at time t;

A_{t-q} = the reported (actual) EPS for the quarter t-q;

F_{t-q} = the recent forecasted EPS for the quarter t-q; and

P_{t-q-1} = the stock price 10 days prior to the quarter t-q.

The negative *MQFEs* imply that analysts' optimism in earnings forecasts has dominated analysts' pessimism at least in terms of the magnitude of the past negative forecast errors, but not necessarily in terms of the frequency of those. So, forming portfolios based only on *MQFEs* may lead to a misclassification problem. For example, suppose that a firm at quarter t has one large negative forecast error 20 quarters before and 19 small positive forecast errors since then, and the magnitude of one negative forecast error outweighs the sum of 19 small positive forecast errors. The firm is likely to be assigned to the optimistic portfolio if the *MQFE* is used as the only formation method. Arguably, it would be more appropriate that the firm be classified into the pessimistic portfolio in this case, considering analysts' dominant tendency toward pessimistic forecasts.

The frequency of negative earnings forecast errors means the number of negative forecast errors for 20 quarters prior to the earnings announcement, and the maximum frequency is accordingly 20. The higher frequency indicates the higher likelihood that analysts on average generate optimistic contemporaneous earnings forecasts, resulting in negative contemporaneous forecast errors. Using the frequency measure as an independent portfolio formation method is not free of the misclassification problem. For instance, suppose that a firm at quarter *t* has an even distribution of negative and positive forecast errors over 20 quarters prior to the quarter *t* – that is, 10 negative and 10 positive forecast errors. Also assume that the magnitudes of the 10 negative forecast errors far outweigh those of the 10 positive. If the frequency measure is strictly applied, the firm will be classified into a rational portfolio meaning that analysts' forecasts have been unbiased. This classification is, however, problematic. The fact that when analysts overestimate the actual earnings they persistently do it by a greater amount than when they underestimate the actual earnings is itself a form of analysts' forecast bias more leaning toward optimistic forecasts.

The above discussions naturally suggest that a portfolio formation method combining the two measures (*MQFE* and frequency) will do a better job on forming portfolios that proxy analysts' forecasting behavior prior to the quarterly earnings announcement. Panels A and B of Table 2 present a summary of the *MFFE* method.

4.2.2 Portfolio Formation

I first pool all observations (firm-quarters) and then rank them on the basis of the two measures: $MQFE_{t,20}$ and the frequencies of negative forecast errors. The ranking process using each measure produces the quintile groups of firm-quarters where the quintiles of each measure represents the variability of analysts' forecasting behavior from the most optimistic to the most pessimistic group in the ranking order. In Panel A of Table 2, for both the *MQFE* and frequency measures Quintile 1 (Q1) indicates the quintile group containing the most optimistic firm-quarters, while Quintile 5 (Q5) indicates the quintile group including the most pessimistic firm-quarters.

When I combine the two measures, I end up having a contingency table containing 25 subsets – all possible combinations of the *MQFE*-based and the frequency-based rankings. The firm-quarters in the cell (Q1, Q1) are observations that are expected to have the most optimistic contemporaneous forecast errors, while the cell (Q5, Q5) contains firm-quarters that are expected to be followed by the most pessimistic contemporaneous forecast errors [Panels A and B of Table 2]. The numbers in parentheses indicate firm-quarters and number of firms, respectively.

Given the possible combinations as in Panel A of Table 2, I assign firm-quarters into 5 portfolios on the basis of both the magnitude and the frequency of the past 5-year forecast errors. P1 (P5) indicates the most optimistic (pessimistic) portfolio that consists of firm-quarters with larger negative (positive) *MQFE*s and higher (lower) frequencies of negative forecast errors over the 20-quarter period prior to the earnings announcement. Whether these are useful depends upon whether they have predictive power for the contemporaneous forecast errors. As we shall see later, from the statistical point of view, P1 is an optimistic portfolio and P5 is a pessimistic portfolio. Labels of P2, P3, and P4 are, however, less obvious than those of P1 and P5, since inferences from the *MQFE* measure and the frequency measure are more controversial in case of the former portfolios than the latter. I, hence, put more emphasis on P1 and P5 than the rest in testing the proposed hypotheses. The notations P1-P5 have consistent meanings hereafter. P1 means the most optimistic portfolio and P5 is defined as the most pessimistic portfolio no matter what kind of portfolio formation method is used.

4.3 Mean-Frequency Time-Series (MFTS) Method

As noted earlier in this chapter, the *MFFE* method might face serious Type II error problem resulting from misclassification. Investors may consider other factors when imputing bias to analysts' forecasts, so that the *MFFE* may not adequately capture analysts' forecast bias that investors perceive. In the following sections I introduce a time-series regression model used by De Bondt and Thaler (1990; *DBT* hereafter) and develop another classification method by combining the *DBT* model with the *MFFE* method to reduce Type II error.

4.3.1 Estimation of De Bondt and Thaler (DBT) Model

The following *DBT* model is the restatement of Equation (2-3):

$$A_t - A_{t-1} = \delta_0 + \delta_1(F_t - A_{t-1}) + e'_t \tag{4-2}$$

$$\Leftrightarrow AEC_t = \delta_0 + \delta_1 FEC_t + e'_t \tag{4-3}$$

where

AEC_t = the actual earnings change from quarter *t-1* to quarter *t*;

FEC_t = the analyst-forecasted earnings change from quarter *t-1* to quarter *t*; and

Other terms are as defined earlier.

For each firm-quarter observation, the De Bondt and Thaler (*DBT*) model is estimated over the 20 quarters prior to the contemporaneous earnings announcement. Negative intercepts ($\delta_0 s$), in general, indicate optimistic analysts' forecasts during the period, holding the slope coefficient (δ_1) constant, say "1" for simplicity. Holding δ_0 constant, say "0", slope coefficients ($\delta_1 s$) less than one and greater than zero also suggest that analysts have been optimistic. Together with the condition of $0 < \delta_1 <= 1$, larger negative $\delta_0 s$ mean that analysts have produced overly optimistic forecasts. As a result, firm-quarters with negative $\delta_0 s$ and positive but less-than-one $\delta_1 s$ are assigned to optimistic portfolios. More specifically, I rank $\delta_0 s$ and $\delta_1 s$ in quintiles respectively and obtain a table that has possible combinations (25 subsets) of δ_0 and δ_1 quintiles [Panel C of Table 2]. Lower δ_0 quintiles are likely to have negative $\delta_0 s$ implying analysts' optimism. Similarly, lower δ_1 quintiles are expected to contain $\delta_1 s$ smaller than one and larger than zero, again indicating analysts' optimism.

Conversely, positive $\delta_0 s$ and greater-than-one $\delta_1 s$ are indications of analysts' pessimism during the past 5 years prior to the earnings announcement. Higher δ_0 and δ_1 quintiles, therefore, are likely to capture analysts' pessimism. Based on the newly formed subsets, I create quintile portfolios over the 5-year formation period. Again, portfolios P1 through P5 represent the range of analysts' forecasting behavior from the most optimistic to the most pessimistic.

4.3.2 Portfolio Formation

After applying the *MFFE* and the *DBT* methods, I end up with ten portfolios: 5 from the former and 5 from the latter. I draw another contingency table having 25 subsets of the two portfolio formation methods as shown in Panel D of Table 2. To make sure that the new portfolios minimize possible misclassification problems from applying either the *MFFE* or the *DBT* model, I select the 5 diagonal subsets to form 5 new portfolios. The new P1 includes the firm-quarters that were classified as P1 by both the *MFFE* method and the *DBT* model. Similarly, the firm-quarters, ranked as P5 in both the *MFFE* and the *DBT* model, are placed into the new P5. Although this new method (*MFTS*) decreases the sample size, it is useful to perform a robustness test for the main portfolio formation method – the *MFFE* method.

Chapter 5

Data and Abnormal Return Measures

5.1 Data

The sample used in this research includes quarterly analysts' consensus earnings forecasts and reported (or actual) earnings per share (*EPS*), as well as price and return data. Quarterly analysts' consensus earnings forecasts and reported *EPS* are taken from the Institutional Brokers Estimate System (*I/B/E/S*). Assuming that firms announce their quarterly earnings before the beginning of the next quarter, I collect the most recent quarterly consensus earnings forecasts that are available on the *I/B/E/S* Summary tape. Analysts' earnings forecast errors are calculated using reported earnings from the *I/B/E/S* Actual tape. Stock price and return information are extracted from the Center for Research in Security Prices (*CRSP*) daily database. *COMPUSTAT* is also used to collect the market value and the book value of common equity.

As noted by some studies, *I/B/E/S* has a reporting lag problem. According to O'Brien (1988), average reporting lag between analysts' forecast dates and *I/B/E/S* reporting dates is 34 trading days, and it has a standard deviation of 44.5 trading days. She argues that the reporting lag may induce a measurement error in analysts' forecasts. Abarbanell and Bernard (1992) contend that such measurement error might cause a downward bias on the coefficient of analysts' forecast changes used in De Bondt and Thaler (1990), and this might induce overreaction results. Although Cornell and

Landsman (1989) report that the average reporting lag of *I/B/E/S* is improved to 10 days, it would be appropriate for researchers to endeavor to minimize the lag problem when they collect earnings forecast information from *I/B/E/S*. To make sure that earnings forecasts for the contemporaneous quarter reflects recent earnings information, the *I/B/E/S* consensus forecasts closest to the earnings announcement dates are used. Alleviating the reporting lag problem results in better measurement of unexpected new earnings information by decreasing the expected portion of new earnings information.

To be included in the final sample, each firm should have at least 21 consecutive quarters of data for actual and forecasted EPS on *I/B/E/S*. This ensures that firm-quarters are properly classified into portfolios on the basis of either the *MFFE* or the *MFTS* method. In addition, for every firm in the sample, 250 days of *CRSP* return data prior to the quarterly earnings announcement is needed for the calculation of market-model adjusted 3-day cumulative abnormal returns (*CARs*).[48] The initial number of observations is 137,065 firm-quarters (7447 firms) that are available on both *I/B/E/S* and *CRSP*. Due to the look-back portfolio formation process, 20 firm-quarters of data are removed from each firm and this reduces the sample to 47,118 firms-quarters (2284 firms). After removing observations with missing values, the sample size is further reduced to 39,249 firm-quarters (2002 firms).

My sample selection procedures and the use of *I/B/E/S* / *CRSP* / *COMPUSTAT* intersected data may introduce survivorship bias, but related literature has shown that

[48] The 3-day *CARs* are computed by adding market-model adjusted daily abnormal returns from -2 (2 days prior to the earnings announcement) to 0 (the earnings announcement) [see Section 5.2].

survivorship bias has little effect on tests for stock price performance [Bernard and Thomas (1989); Ball and Kothari (1989)].

COMPUSTAT is used to extract firm-quarters' equity information: the book value of equity (*BVE*) and the market value of equity (*MVE*). The firms included in the final sample are, as a result, the ones listed on the *I/B/E/S* tape for at least 21 quarters, and on the *CRSP* daily return tape for at least 250 days prior to the earnings announcement. They should also have *BVE* and *MVE* available on *COMPUSTAT*. After intersecting the sample of 39,249 firm-quarters from *I/B/E/S* and *CRSP* with the quarterly *COMPUSTAT* data, quite a few observations are further removed, and the final sample size for the *MFFE* method is 34,605 firm-quarters (1882 firms).[49] The sample covers a 12-year period from 1990 to 2001. One enhancement over other studies [Cornell and Landsman (1989); Moses (1991)] is that I do not restrict the sample to firms listed on the *NYSE*, *AMEX*, and *NASDAQ* with December fiscal-year ends.

Given the above argument, the sample includes quarterly analysts' earnings forecasts, quarterly actual earnings, daily stock returns, the market value of equity (*MVE*), the book-to-market ratio, and other necessary variables subject to the following criteria:

1) The final sample firms are required to be covered on *CRSP*, *COMPUSTAT*, and *I/B/E/S*.

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[49] The final sample for the *MFTS* method is formed by intersecting the sample [27,635 firm-quarters (2009 firms)] from the *DBT* model with the sample [34,605 firm-quarters (1882 firms)] from the *MFFE*. As shown on the diagonal in Panel D of Table 2, the final sample for the *MFTS* consists of 8997 firm-quarters. Note that the *MFFE* sample size in Panel A of Table 6 is 34,339 because 266 observations in 1989 are excluded from analysis. Similarly, the *MFTS* sample size in Panel B of Table 6 equals 8995, since 2 observations in 1989 are dropped.

2) Quarterly analysts' consensus earnings forecasts and actual earnings are available from *I/B/E/S* summary forecast and actual earnings data tapes. Each firm-quarter observation is preceded by at least 20 consecutive quarterly earnings observations.
3) Daily security returns and value-weighted market returns are available from *CRSP* for 250 trading days prior to the earnings announcement.

Items 2 and 3 ensure that portfolios can be formed on the basis of analysts' forecasting behavior and that necessary return information is available. They also make it possible to estimate the market-model parameters (i.e., alpha and beta) and calculate the market-model adjusted abnormal returns. As in most earnings announcements literature, 3-day [−2:0] *CARs* are used as the measure of the announcement-period abnormal returns [Chopra, Lakonishok, and Ritter (1992); La Porta (1996)].

5.2 Market-Adjusted Abnormal Returns and Market-Model Adjusted Abnormal Returns

The market-adjusted and market-model adjusted daily abnormal returns for the common stock of firm *i* on day *t* are defined as:

$$AR_{it}^{MA} = R_{it} - R_{mt}, \tag{5-1}$$

$$AR_{it}^{MM} = R_{it} - \left(\hat{\alpha}_{it} + \hat{\beta}_{it} R_{mt}\right), \tag{5-2}$$

where

AR_{it}^{MA} = the market-adjusted abnormal returns of firm *i* on day *t* (= -2, -1, 0);

AR_{it}^{MM} = the market-model adjusted abnormal returns of firm *i* on day *t*;

R_{it} = the rate of return for the common stock of firm *i* on day *t*; and

R_{mt} = the rate of return on the *CRSP* value-weighted market index on day *t*.

For the market-model adjusted abnormal returns, the coefficients $\hat{\alpha}_{it}$ and $\hat{\beta}_{ti}$ are ordinary least squares estimates of firm *i*'s market model parameters estimated over 240 days from 250 days to 10 days prior to the earnings announcement. For each quarterly earnings announcement in a firm, AR_{it}^{MA} and AR_{it}^{MM} are calculated.

I compute 3-day [–2: 0] cumulative abnormal returns for the contemporaneous earnings announcement for firm *i* (CAR_{it}) as follows:[50]

$$CAR_{it} = \sum_{t=1}^{3} AR_{it} \qquad (5\text{-}3)$$

where

$AR_{it} = AR_{it}^{MA}$ or AR_{it}^{MM} .

The 3-day announcement-period *CARs* are, then, used as the dependent variable for the empirical models introduced in Chapter 3.[51]

[50] The use of 3-day [–2: 0] *CAR* is the norm in earnings studies. It is used to measure the announcement-period market reaction to analysts' forecast errors.
[51] I run the empirical models by using both market adjusted and market-model adjusted *CARs* as the dependent variable. I later report the empirical results from the models using the market-model adjusted *CARs*, since main results are not affected by different measures of abnormal returns. In addition, the choice of announcement windows {e.g., 2-day [-1:0] or 1-day [0] *CARs*} does not affect the main results.

Chapter 6

Empirical Tests

6.1 Descriptive Statistics

Table 3 summarizes descriptive statistics of 3-day cumulative abnormal returns (*CARs*), mean quarterly forecast errors (*MQFEs*), contemporaneous forecast errors (*FEs*), the market value of equity (*MVE* or *Size*), the logarithm of *MVE* (*logSize*), and book-to-market ratios (*BtoM*), and other variables over time and across the 5 portfolios – P1, P2, P3, P4, and P5. As demonstrated in Chapter 4, these 5 portfolios are formed by either the *MFFE* or *MFTS* methods. In either formation method, P1, P2, P3 represent the optimistic portfolios, while P4 and P5 are the pessimistic portfolios. P1 and P5 are two extreme portfolios that indicate the most optimistic and the most pessimistic portfolios respectively. The classification of P2 and P3 into the optimistic portfolios is somewhat arbitrary (discussed below).

Panel A of Table 3 reports overall descriptive statistics of major variables. Consistent with common findings in existing earnings literature, the grand means of *MQFE* and *FE* are significantly negative – i.e., analysts are, on average, optimistic and analysts' optimism persists. Recall that the forecast error is defined as $A_t - F_t$. Negative *MQFEs* and *FEs* imply historical and contemporaneous optimistic analysts' forecasts, respectively. Notice that the mean *CAR* is significantly positive, while the mean *FE* is significantly negative. This has an important implication regarding the test of the *NEH* versus the *REH*. If investors are naïve in reaction to analysts' forecasting behavior, the negative *FE* should lead to negative market reaction – i.e., negative *CAR*. The negative *FE* is, instead, associated with the positive *CAR*. This suggests that investors have discounted analysts' optimism and the *NEH* does not receive support. This is the first evidence in favor of the *REH*.

Although (–) *MQFEs* outnumbers (+) *MQFEs*, the number of (–) *FEs* is less than that of (+) *FEs*.[52] This suggests that analysts tend to issue pessimistic forecasts more frequently, while the absolute magnitudes of optimistic forecast errors are larger than those of pessimistic ones. Given this observation about frequency versus magnitude, it is not obvious whether analysts' earnings forecast bias is characterized by optimism. Therefore, either *MQFEs* or the frequency of (–) *FEs* alone may not be sufficient to characterize analysts' forecasting behavior. Also notice that 4247 *FEs* – about 12% of total observations – are zero. Non-trivial number of analysts' forecasts accurately hit the actual earnings. In what circumstances are unbiased forecasts issued? Is this an indication of earnings management? Individual characteristics of analysts might be the main reason, or certain firm characteristics may play a key role in producing unbiased forecasts. Investigating these issues warrants future research.

Panel B of Table 3 shows that absolute values of average *MQFE* ($AMQFE_T$) and average *FE* (AFE_T) tend to decrease over time, indicating that analysts' optimistic forecast bias has been mitigated.[53] Kendall's *Tau'*s between $AMQFE_T$ and time (i.e.,

[52] Note that I use the notation (-) for "negative" and the notation (+) for "positive".
[53] Notice I use a subscript "*T*" with the variable names to indicate that variables are time-wise, not portfolio-wise. I use a subscript "*P*" to indicate portfolio-wise variables. For example, $AMQFE_T$ indicates average *MQFE* for a specific year "*T*", while $AMQFE_P$ means average *MQFE* for a portfolio "*P*".

years) and AFE_T and time are −0.91 and −0.64 significant at the conventional significance levels. Although average *logSize* ($AlogSize_T$) exhibit some extent of decreasing patterns over time (Kendall's *Tau* is −0.42 significant at the 10% level), there seems to be no significant trend for either average *CAR* ($ACAR_T$). Similarly, average *BtoM* ($ABtoM_T$) have no significant trend.

On the other hand, Panel C of Table 3 documents that portfolios possess some distinct characteristics in terms of the firm size and the book-to-market ratio. The average *CAR* ($ACAR_P$) and average *BtoM* ($ABtoM_P$) tend to be larger for the optimistic portfolios than for the pessimistic ones. The average firm size ($AlogSize_P$) monotonically increases as the portfolios change from P1 to P2 to P3 to P4 to P5. In sum, $ACAR_P$ is negatively associated with $AlogSize_P$ and positively with $ABtoM_P$. The former relation indicates the size effect, while the latter implies the profitability of the value-firm investments [Fama and French (1993, 1995)]. Panels D, E, F of Table 3 contain descriptive statistics using the *MFTS* method and show very consistent results with ones using the *MFFE*.

6.2 Validity of Portfolio Formation Methods

Developing a valid portfolio formation method is critical to examine the two main behavioral issues in this study: 1) Persistent bias; 2) Investors' reaction to analysts' forecasting behavior. The validity of the two formation methods – *MFFE* and *MFTS* – depends on their predictive power for the contemporaneous average forecast errors (AFE_P) and the percentage of the negative contemporaneous *FEs* [*%(–FE)*]. For instance, the most optimistic portfolio (P1) should have the largest negative mean of contemporaneous *FEs* and the highest *%(–FE)* for my portfolio formation methods (*MFFE* and *MFTS*) to be valid. Panel C of Table 3 shows that for P1, the mean contemporaneous *FE* is indeed significantly negative, and is the most negative. *%(–FE)* is also highest. The binomial tests in Table 4 indicate that the portfolio P1's *%(–FE)* is 53% for the *MFFE* and 55% for the *MFTS* and both are significantly greater than 50%. Therefore, P1 is indeed an optimistic portfolio consistent with the predictions of both the *MFFE* and the *MFTS* methods. It should be noted that examining the validity of the portfolio formation methods is a joint test of bias and persistence in analysts' earnings forecasts in the sense that the *MFFE* and the *MFTS* are based on historical analysts' forecast bias that continues into the current period.

As predicted by the *MFFE* and the *MFTS*, P4 and P5 have significantly positive AFE_P and the percentage of positive *FE*s [*%(+FE)*] outweighs that of *%(–FE)*. The magnitudes of AFE_P and *%(+FE)* for P5 are greater than those for P4. These results are exactly what was intended by the *MFFE* and the *MFTS* methods. The results in Panels C and F of Table 3, therefore, suggest that the *MFFE* and the *MFTS* methods are valid in the sense of providing statistically reliable predictions of contemporaneous forecast errors, at least for portfolios P1, P4, and P5. More importantly, this implies that the persistent bias presumption manifested in the *MFFE* and the *MFTS* methods receives support.

For P2 and P3, the predictability of the two methods is not as clear as the other portfolios. For both the *MFFE* and the *MFTS* methods, *%(–FE)* is not consistent with the predictions of the two methods. Actually, it is contradictory. While AFE_P for P2 and P3 have predicted signs (i.e., negative), *%(–FE)* is smaller than or not significantly different from *%(+FE)*. According to Panels C and F of Table 3, *%(–FE)*'s for P2 and P3 are 48% and 46% for the *MFFE* and 49% and 45% for the *MFTS*. The binomial tests in Table 4 indicate that those *%(–FE)*'s are significantly less than 50% except for *%(–FE)* for P2 formed by the *MFTS*, which is not significantly different from 50%. P2 and P3 are, thus, not as convincing as the others in terms of predictive power.

I classify P2 into an optimistic portfolio because its AFE_P's (–0.00057 for the *MFFE* and –0.00054 for the *MFTS*) are significantly negative [and more negative than the grand mean of forecast errors (–0.00048)] and the difference between *%(–FE)* and *%(+FE)* is not so wide. As pointed out earlier, Panel B of Table 4 shows that P2's *%(–FE)* is not significantly different from *%(+FE)*.

Although P3 has significantly negative AFE_P, it is smaller than the grand mean (–0.00048) in terms of absolute value, and *%(–FE)* is significantly smaller than *%(+FE)* for both the *MFFE* and the *MFTS* methods [Panels C and F of Table 3 and Panels A and B of Table 4]. It is, thus, difficult to assign P3 into either an optimistic or a pessimistic portfolio. I arbitrarily assign P3 into an optimistic portfolio, since it has significantly negative AFE_P whose definition is consistent with the definition of analysts' optimism in this study.[54] It would be, however, also possible for one to argue that P3 may be classified into a rational portfolio. But, it does not receive any statistical support.

[54] As a result, there is no rational portfolio in the 5 portfolios (at least from the statistical point of view). This, however, should not be a problem because the main objective of the dissertation is to find the relation of investors' reaction to analysts' biased forecasting behavior, not to unbiased forecasting behavior.

The persistent bias in analysts' forecasts is an important and necessary condition to examine investor rationality in response to analysts' forecast errors. Evidence that the *MFFE* and the *MFTS* methods are valid measures of predicting the contemporaneous forecast errors suggests that analysts' forecast bias is persistent. Given that analysts tend to make persistent upward (optimistic) or downward (pessimistic) bias in their forecasts, investors' reaction to analysts' forecast errors is expected to reveal investor rationality in forming conditional earnings expectations of their own.

At least for the extreme portfolios P1 and P5, the predictability of the two portfolio formation methods is obvious. P4 is also as predictable in terms of both mean and frequency of *FEs*. When it comes to the interpretation of empirical results from the multiple regression models used to test the *NEH* against the *REH*, I place more weight on the "extreme" portfolios – the portfolio P1 and the portfolio P5 – to avoid possible debates over the validity of the formation methods especially in case of P2 and P3.

To further examine the persistence in analysts' earnings forecasts, I perform both parametric and non-parametric autocorrelation tests. Panels A and B of Table 5 report results from a nonparametric Chi-square test of autocorrelation between FE_{t-1} and FE_t.[55] If analysts' earnings forecasts do not display any persistent bias, the observed frequencies should equal the theoretical ones. If there are no significant differences between the observed and theoretical frequencies, the Chi-square test fails to reject the null hypothesis that the observed frequencies are equal to the theoretical. But, the data

[55] Gujarati (1988; pp. 373-375).

shows that the Chi-square statistic is significant at the 1% level, and suggests that the signs of *FEs* tend to stay in the same direction between quarter *t-1* and quarter *t*.

I also perform a simple parametric test in Panels C and D of Table 5. The test consists of the estimation of the first-order autoregressive model [i.e., AR (1)], both on the pooled sample and each portfolio, to see whether an autocorrelation structure exists between FE_{t-1} and FE_t. I found that the autocorrelation between the consecutive *FE*s was positive and highly significant, indicating the signs of *FEs* do not change rapidly. These results confirm that analysts' forecast bias is persistent.

To see whether there is clustering within portfolios or across portfolios on various factors that might influence analysts' forecast bias, I compute three Herfindahl indexes: 1) Time Herfindahl; 2) Industry Herfindahl; 3) Stock Exchange Herfindahl [Table 6]. Time Herfindahl index measures the relative concentration of a portfolio over the 12-year study period. Industry Herfindahl index calibrates the relative concentration of an industry sector across portfolios, while Stock Exchange Herfindahl gauges the relative concentration of a stock exchange across portfolios. The three Herfindahl indexes are calculated as follows:

$$H_P = \sum_{t=1}^{12} \left(\frac{FREQ_{t,P}}{FREQ_{sum,P}} \right)^2 \tag{6-1}$$

$$H_{IND} = \sum_{p=1}^{5} \left(\frac{FREQ_{p,IND}}{FREQ_{sum,IND}} \right)^2 \tag{6-2}$$

$$H_{EX} = \sum_{p=1}^{5} \left(\frac{FREQ_{p,EX}}{FREQ_{sum,EX}} \right)^2 \tag{6-3}$$

where

H_P = the Herfindahl index for a portfolio *P* where *P* = *P1, …, P5*;

H_{IND} = the Herfindahl index for an industry *IND* where *IND* = 1, …, 11;

H_{EX} = the Herfindahl index for a stock exchange *EX* where *EX* = *NYSE*, *AMEX*, *NASDAQ*;

$FREQ_{t,P}$ = the marginal frequency of a portfolio *P* in year *t*; and

$FREQ_{p,IND}$ = the marginal frequency of an industry *IND* for a portfolio *p*;

$FREQ_{p,EX}$ = the marginal frequency of a stock exchange *EX* for a portfolio *p*;

$FREQ_{sum,P}$ = the aggregate frequency of portfolio *p* over the 12-year period;

$FREQ_{sum,IND}$ = the aggregate frequency of an industry *IND* across portfolios; and

$FREQ_{sum,EX}$ = the aggregate frequency of an exchange *EX* across portfolios.

For Time Herfindahl index, portfolios for which all observations fall in a specific year will have a Herfindahl index of 1. Portfolios, which have observations spread evenly through time, will have a Herfindahl index of 0.0833. To illustrate, suppose that all observations in P1 are clustered in 1990 so that no observations in P1 can be found in any other years. The marginal frequency of P1 in 1990 ($FREQ_{1990,P1}$) equals the aggregate frequency of P1 over the 12-year period ($FREQ_{sum,P1}$), while the marginal frequencies of P1 for any other years are zero. Then, the Time-Herfindahl index for P1 (H_{P1}) equals one. If all observations in P1 are evenly spread across years, H_{P1} becomes $\frac{1}{12}$ (=0.0833). The data in Panels A and B of Table 6 suggests that all portfolios are well spread over the sample time period and implies that the persistent bias in analysts' forecasts is not dominated by a specific year.

Industry Herfindahl and Stock Exchange Herfindahl indexes provide similar evidence. Panels C~F reflect that industries and exchanges seem to be well scattered across portfolios, since Industry Herfindahl and Stock Exchange Herfindahl indexes are, in most cases, close to 0.2.[56] In other words, industry and stock exchange factors are not significant determinants of the persistent bias in analysts' forecasts.

It is reasonable to say that past forecasting behavior, measured by the *MFFE* or the *MFTS*, has predictive ability with respect to contemporaneous analysts' earnings forecasts. Note again that I use "forecasting behavior" as a synonym of persistent bias in analysts' forecasts. Recognizing the existence of persistent bias in analysts' earnings forecasts, I turn to the issue of how investors are expected to react to analysts' forecasting behavior.

6.3 Empirical Tests of NEH versus REH

As discussed in Chapter 3, three multiple regression models are estimated to test the *NEH* versus the *REH*. The following are the restatements of the three models described in Chapter 3 [i.e., Equations (3-3), (3-4), and (3-5)]:[57]

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[56] The Herfindahl index for an industry or an exchange will be "0.2" if observations in the same industry or exchange are equally distributed across portfolios, while it will be "1" if observations in the same industry or exchange are clustered in a specific portfolio.

[57] I reexamined the three models with time dummies for quarters and the inclusion of time dummies does not alter the main findings of the models without dummies. The models including time dummies are econometrically more appropriate since by doing so the error terms have zero means every quarter. I also performed autocorrelation test on the error terms for the three models (with time dummies) and found no

$$CAR_t = \alpha_1 P_1 + \alpha_2 P_2 + \alpha_3 P_3 + \alpha_4 P_4 + \alpha_5 P_5 + \beta_1 diffSize_t + \beta_2 diffBtoM_t + u_t \quad (6\text{-}4)$$

$$CAR_t = a_1 P_1 + a_2 P_2 + a_3 P_3 + a_4 P_4 + a_5 P_5 + b_1 \frac{FE_t}{STD_t}$$

$$+ b_2 diffSize_t + b_3 diffBtoM_t + \upsilon_t \quad (6\text{-}5)$$

$$CAR_t = a_1' + a_2' P_2 + a_3' P_3 + a_4' P_4 + a_5' P_5 + b_1' \frac{FE_t}{STD} + b_2' \frac{FE_t}{STD} P_2 + b_3' \frac{FE_t}{STD} P_3$$

$$+ b_4' \frac{FE_t}{STD_t} P_4 + b_5' \frac{FE_t}{STD_t} P_5 + b_6' diffSize_t + b_7' diffBtoM_t + \omega_t \quad (6\text{-}6)$$

Terms are as defined earlier, and firm subscripts are omitted for convenience.

Panel A of Table 7 shows results from the estimation of Equation (6-4). The *NEH* predicts that naïve investors naïvely follow analysts' optimism and their reaction to such optimism (i.e., negative forecast errors=bad news) on average leads to negative *CAR*s, while naïve investors' reaction to analysts' pessimism (i.e., positive forecast errors=good news) results in positive *CAR*s.[58] Under the *NEH*, therefore, the market reaction to the earnings announcement would be negative for optimistic portfolios (e.g., P1) and positive for pessimistic portfolios (e.g., P5). Specifically, the *NEH* expects that α_5 is greater than α_1. The *REH*, however, hypothesizes that rational investors do not perceive analysts' optimism or pessimism as bad news or good news, since they fully adjust for analysts' forecasting behavior (i.e., optimism or pessimism) so that the contemporaneous negative

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significant autocorrelation structure. For the *MFFE* method, the correlations between the contemporaneous error term and the lagged error term were 0.044, -0.015, and 0.096 respectively for the three models and they are all insignificant. Similar results were found for the *MFTS* method. Durban-Watson statistics also suggest that there is no first-order autocorrelation.

[58] Recall that the average forecast error for P1 (the most optimistic portfolio) is significantly negative, while the average forecast error for P5 (the most pessimistic) is significantly positive.

or positive forecast errors do not have an impact on rational investors' reaction to the earnings announcement. As a consequence, under the *REH*, the average market reaction (i.e., α_1) for P1 should not be significantly different from α_5.

The regression results in Panel A of Table 7 indicate that no pair-wise comparison between portfolio abnormal returns is significant; the *NEH* that investors are naïve followers of analysts' forecasts is rejected. I also perform Scheffe's multiple comparison method to test all possible contrasts at the same time. Considering that the portfolio sample sizes are unequal, Scheffe's method may be preferred to other pair-wise comparisons (e.g., F-tests or Tukey's method). The results from Scheffe's method also display no significantly different pairs. Also recall that the negative mean *FE* is associated with the positive mean *CAR* (Panel A of Table 3). Therefore, the *NEH* is rejected in favor of the *REH*.

Panel B of Table 7 documents the regression results from estimating Equation (6-5). According to the *MFFE* the estimate of the dummy variable P1 (i.e., fixed or intercept market effect for P1) is significantly larger than that of P5 – i.e., $a_1 > a_5$. For both the *MFFE* and the *MFTS*, a_1 (0.00359 and 0.00427) is greater than a_5 (0.00178 and 0.00214), and the F-test for the *MFFE* rejects the null hypothesis (Ho: $a_1 = a_5$) at the 5% level. These are in compliance with the predictions of the *REH*. But, the F-test for the *MFTS* fails to reject Ho: $a_1 = a_5$ with p-value of 0.1848. In addition, the results from Scheffe's multiple comparisons disclose that all pairs of the portfolio dummy estimates are not significantly different from each other – i.e., $a_1 = a_2 = a_3 = a_4 = a_5$. Therefore, the data does not strongly reject the *NEH*. These results are, however, based on the assumption that the marginal market effects [slopes in Equation (6-5)] of all portfolios are the same.

Equation (6-6) releases the assumption of equal portfolio slopes and uses P1 as the reference portfolio (I do not display all possible regression results based on different reference portfolios because the focus is on the extreme portfolios). Panels C-1 and C-2 of Table 7 indicate that for the *MFFE* a_1' (0.00359) is significantly greater than $a_1' + a_5'$ (0.00199) with p-value of 0.0671. They also show that the slope (marginal) market effect of P1 (i.e., b_1'=0.0021) is not significantly different from that of P5 (i.e., $b_1' + b_5'$=0.00179) with p-value of 0.1234. However, the *MFTS* does not fully conform the *MFFE*'s results by failing to reject Ho: $a_1' = a_1' + a_5'$. Moreover, Scheffe's multiple comparisons show no significant pairs of portfolio intercepts. Similar to the findings in Panel B, the data does not strongly reject the *NEH*.

In summary, regressions provide mixed evidence. One model [Equation (6-4)] rejects the *NEH* and supports the *REH*. The other two models, on the other hand, do not strongly reject the *NEH*.

Chapter 7

Conclusions

Prior studies have reported that analysts' earnings forecasts are upward or downward biased, and economic and non-economic incentives have been provided to explain such observed bias. Management access and career (reputation) concerns are, among others, the examples of economic incentives for analysts to issue biased earnings forecasts. Michaely and Womack (1999) and Dechow, Hutton, and Sloan (2000) document that financial analysts of brokerage firms tend to issue more favorable recommendations or earnings growth forecasts due to the underwriting relationships with the company they follow. Scharfstein and Stein (1990) contend that analysts deliberately report earnings forecasts that are closer to or further from the consensus because of career concerns.

Another group of explanations draws from the behavioral finance literature to suggest that analysts suffer from cognitive failures. While De Bondt and Thaler (1990) argue that analysts tend to overreact to new earnings information and their forecasts are thus extreme, Abarbanell and Bernard (1992) and Mendenhall (1991), among others, conjecture that analysts appear to underreact to new earnings information. As discussed earlier, Easterwood and Nutt (1999) reconcile the overreaction and the underreaction views by demonstrating that analysts, in fact, overreact to good news and underreact to bad news. Such systematic overreaction and underreaction results in analysts' optimism in earnings forecasts.

This dissertation explores whether analysts' forecast bias is persistent (i.e., whether the historical record of analysts' forecasting behavior has predictive ability with respect to subsequent forecast errors), and then proposes two competing hypotheses – the *NEH* and the *REH* – to examine how investors respond to the persistent bias in analysts' earnings forecasts, if they are indeed persistent. The *NEH* surmises that investors take analysts' forecasts as unbiased and these naïve investors' earnings expectations are identical to analysts' earnings forecasts. Empirically, this prediction leads to the conclusion that naïve investors' reaction to a given analyst forecast error (holding other factors constant) does not vary with the observed persistent bias in analysts' earnings forecasts – optimistic or pessimistic. Recall that I use the term "analysts' forecasting behavior" as a synonym of "the observed persistent bias in analysts' earnings forecasts".

The *REH*, in contrast, presumes that investors discount or place a premium on the persistent bias, and thus, these rational investors' earnings expectations are different from analysts' earnings forecasts. Specifically, under the *REH* investors' reaction to a given analyst forecast error varies systematically with analysts' forecasting behavior.

The descriptive statistics in Table 3 convey important implications regarding analysts' forecast bias and predictive power of the two portfolio formation methods used in the dissertation. The overall descriptive statistics in Panel A of Table 3 suggest that investors, on average, tend to discount analysts' optimism in earnings forecasts that characterizes average analysts' forecasting behavior. Although the trend is not monotonic, Panels B and E exhibit that average analysts' optimism tends to be attenuated over time. Non-trivial number of zero forecast errors, on the other hand, gives credence to earnings management. In addition, Panels C and F reveal systematic size and book-to-market association with forecast errors.

Panels C and F of Table 3 show that the portfolio formation methods (*MFFE* and METS) successfully create an optimistic portfolio (P1) and a pessimistic one (P5) consistent with the predictions of both formation methods. For P1, the mean of contemporaneous forecast errors (*AFE*) is indeed significantly negative (actually most negative), and the percentage of negative forecast errors is highest, as predicted by both methods. The similar results are found for P5; *AFE* is significantly positive and the percentage of positive forecast errors outweighs that of negative ones. The binomial test of the hypothesis that the probability of getting positive forecast errors equals 0.5 confirms the validity of the formation methods by rejecting the hypothesis for both portfolios. Note again that the validity test of the formation methods is a joint test of analysts' forecast bias and its persistence, in the sense that the formation methods are based on the premise that historical analysts' forecast bias persists into the current period.

The persistence in analysts' earnings forecasts is further examined using various parametric and non-parametric tests. The non-parametric Chi-square tests and the first-order autoregressive models suggest that there is a significant autocorrelation between FE_{t-1} and FE_t. The three Herfindahl indexes provide evidence that each portfolio is well spread over time and across industries and stock exchanges. This reflects that the persistent bias in analysts' earnings forecasts is not characterized by such factors as time, industry, or stock exchanges.

Multiple regression methodology is used to determine whether investors respond differently based on evidence of prior persistent bias in analysts' forecasts. The regressions are intended to contrast naïve investors' reaction to analysts' forecast bias with rational investors' reaction to such bias. Equation (6-4) investigates the average market reactions of optimistic and pessimistic portfolios controlling for size and book-to-market ratio. Unlike Equations (6-5) and (6-6), Equation (6-4) incorporates the impact of the average forecast errors in portfolios into the intercept effect. So, the average *FE*s in respective portfolios are reflected in the magnitudes of the dummy variable coefficients (α_1,…, α_5). The *NEH* predicts that the coefficient for P1 (α_1) should be smaller than that for P5 (α_5), since naïve investors' reaction to analysts' optimism (pessimism) will, on average, be negative (positive).[59]

The *REH*, on the other hand, conjectures that α_1 and α_5 will be statistically indistinguishable, since rational investors do not perceive analysts' optimism or pessimism as bad news or good news. In other words, rational investors fully discount analysts' contemporaneous optimistic forecasts or place a fully-adjusted premium on analysts' contemporaneous pessimistic forecasts, so that the corresponding negative (optimistic) or positive (pessimistic) forecast errors do not influence rational investors' reaction. The regression results support the *REH*. This is consistent with the implication of the negative relationship between the grand mean of analysts' forecast errors and the grand mean of the 3-day cumulative abnormal returns (*CARs*).

[59] Note that analysts' optimism (negative forecast errors) indicates bad news, while analysts' pessimism (positive forecast errors) conveys good news.

Equations (6-5) and (6-6) enhance Equation (6-4) by including the contemporaneous forecast errors as an explanatory variable. As shown in Table 1, given a forecast error (*FE*), naïve and rational investors' reactions to prior bias in analysts' forecasts can be contrasted. Under the *NEH*, given an *FE*, investors' reaction to analysts' optimism should equal that to analysts' pessimism: $CAR_t |_{NEH}^{OPT} = CAR_t |_{NEH}^{PESS}$. Under the *REH*, given an *FE*, investors will adjust for analysts' optimism or pessimism. As a result, given an *FE*, rational investors' reaction to analysts' optimism (pessimism) should be larger (smaller) than naïve investors' reaction to analysts' forecast bias: $CAR_t |_{REH}^{OPT}$ > $CAR_t |_{NEH}$ > $CAR_t |_{REH}^{PESS}$. The estimated parameters and pair-wise comparisons of Equations (6-5) and (6-6) do not strongly reject the *NEH*. While the *MFFE* results reject the *NEH* in favor of the *REH*, the *MFTS* results do not confirm it. With evidence of the persistent bias in analysts' earnings forecasts, the regression results suggest that the functional form [$CAR_t = f(FE_t)$] commonly used in earnings literature may not appropriately capture the effect of real unexpected earnings information (i.e., investors' expectation errors as opposed to analysts' forecast errors) on stock returns.

For the non-extreme portfolios (P2, P3, and P4) the data does not yet provide a clear cut-off for either the *NEH* or the *REH*. Actually, it shows results that are not predicted by either the *NEH* or the *REH*. Having known that the extreme-portfolio case does not strongly reject the *NEH*, I speculate that investors will show some type of quasi-rational response to less extreme analysts' forecasting behavior. If investors had perceived less extreme behavior as unbiased, the market reaction for P1 should have been equal to that for P3. If investors had fully adjusted for the persistent bias of analysts' forecasts, the market reaction for P1 should have dominated that for the P3. The data in Panel C of Table 7 shows that the market reaction for P3 actually dominates that for P1. For instance, P3 has greater market reaction than P1 with respect to both fixed (a_1' versus $a_1' + a_3'$) and marginal effects (b_1' versus $b_1' + b_3'$). Although a_1' and $a_1' + a_3'$ are not statistically different, b_1' and $b_1' + b_3'$ are significantly different for both the *MFFE* and *MFTS* methods at the 5% level. This implies that for positive forecast errors the market reaction for P3 dominates that for P1, and this result is not consistent with either the *NEH* or the *REH*. Therefore, the simple dichotomous framework I employed (*NEH* versus *REH*) has a limit to thoroughly examine investors' reaction to analysts' forecasting behavior.

The limit of my dissertation, however, provides promising opportunities for future research. One may argue that there exist unidentified (or unidentifiable) risk factors beyond the dimensions where current risk factors – size, book-to-market ratio, and momentum effects – are identified. Time periods, industry concentration, or exchange listings may be potential candidates that drive the differences in the market reaction across portfolios although it turns out that they are not significant factors to explain idiosyncratic market reactions. It would be interesting to investigate whether (and/or how) the characteristics (e.g., experience, brokerage relationship, age, reputation, etc.) of individual analysts are associated with portfolios formed on the basis of analysts' bias in consensus earnings forecasts.

BIBLIOGRAPHY

BIBLIOGRAPHY

Abarbanell, Jeffery S., 1991, Do analysts' earnings forecasts incorporate information in prior stock price changes?, Journal of Accounting and Economics 14, 147-165.

Abarbanell, Jeffery S., and Victor L. Bernard, 1992, Tests of analysts' overreaction / underreaction to earnings information as an explanation for anomalous stock price behavior, Journal of Finance 47, 1181-1207.

Ackert, Lucy F., and George Athanassakos, 1997, Prior uncertainty, analyst bias, and subsequent abnormal returns, Journal of Financial Research 20, 263-273.

Ackert, Lucy F., and William C. Hunter, 1995, Rational expectations and security analysts' earnings forecasts, Financial Review 30, 427-443.

Alexander, Jr., John C., 1992, Earnings surprise, market efficiency, and expectations, The Financial Review 27, 475-502.

Ali, Ashiq, April Klein, and James Rosenfeld, 1992, Analysts' use of information about permanent and transitory earnings components in forecasting annual EPS, Accounting Review 67, 183-198.

Ball, R., and S. P. Kothari, 1989, Nonstationary expected returns: Implications for tests of market efficiency and serial correlation in returns, Journal of Financial Economics 25, 51-74.

Barber, Brad M., and John D. Lyon, 1997, Detecting long-run abnormal stock returns: The empirical power and specification of test statistics, Journal of Financial Economics 43, 341-372.

Basu, Sudipta, 1997, The conservatism principle and the asymmetric timeliness of earnings, Journal of Accounting and Economics 24, 3-37.

Bauman, W. Scott, and Richard J. Dowen, 1994, Security analyst forecasts and the earnings yield anomaly, Journal of Business Finance & Accounting 21, 283-291.

Beaver, William H., Roger Clarke, and William F. Wright, 1979, The association between unsystematic security returns and the magnitude of earnings forecast errors, Journal of Accounting Research 17, 316-340.

Bernard, V., and J. Thomas, 1989, Post-earnings-announcement drift: Delayed price response or risk premium?, Journal of Accounting Research 27, 1-36.

Bernard, V., and J. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, Journal of Accounting and Economics 13, 305-340.

Brav, Alon, and Paul A. Gompers, 1997, Myth or reality? The long-run underperformance of initial public offerings: Evidence from venture and nonventure capital-backed companies, Journal of Finance 52, 1791-1821.

Brown, Lawrence D., and Michael S. Rozeff, 1978, The superiority of analyst forecasts as measures of expectations: Evidence from earnings, Journal of Finance 33, 1-16.

Brown, Lawrence D., and Michael S. Rozeff, 1979, Adaptive expectations, time-series models, and analyst forecast revision, Journal of Accounting Research 17, 341-351.

Brown, Lawrence D., 1996, Analyst forecasting errors and their implications for security analysis: An alternative perspective, Financial Analysts Journal 52, 40-47.

Brown, Lawrence D., Robert Hagerman, Paul Griffin, and Mark Zmijewski, 1987, Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings, Journal of Accounting and Economics 9, 61-87.

Brown, Stewart L., 1978, Earnings changes, stock prices, and market efficiency, Journal of Finance 33, 17-28.

Butler, Kirt C., and Larry H. P. Lang, 1991, The forecast accuracy of individual analysts: Evidence of systematic optimism and pessimism, Journal of Accounting Research 29, 150-156.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, Journal of Finance 51, 1681-1713.

Cheng, C.S. Agnes, William S. Hopwood, and James C. McKeown, 1992, Non-linearity and specification problems in unexpected earnings response regression model, The Accounting Review 67, 579-598.

Clement, Michael B., 1999, Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?, Journal of Accounting and Economics 27, 285-303.

Chopra, Navin, Josef Lakonishok, and Jay R. Ritter, 1992, Measuring abnormal performance: Do stocks overreact?, Journal of Financial Economics 31, 235-268.

Collins, Daniel W., and S. P. Kothari, 1989, An analysis of intertemporal and cross-sectional determinants of earnings response coefficients, Journal of Accounting and Economics 11, 143-181.

Collins, Daniel W., S. P. Kothari, Jay Shanken, and Richard G. Sloan, 1994, Lack of timeliness and noise as explanations for the low contemporaneous return-earnings association, Journal of Accounting and Economics 18, 289-324.

Conover, W. J., 1980, “Practical nonparametric statistics,” 2ed, John Wiley & Sons, Inc., New York.

Conrad, Jennifer, and Gautam Kaul, 1993, Long-term market overreaction or biases in computed returns?, Journal of Finance 48, 39-63.

Conroy, Robert, and Robert Harris, 1987, Consensus forecasts of corporate earnings: analysts' forecasts and time series methods, Management Science 33, 725-738.

Cornell, Bradford, and Wayne R. Landsman, 1989, Security price response to quarterly earnings announcements and analysts' forecast revisions, Accounting Review 64, 680-692.

Cox, Don R., and David R. Peterson, 1994, Stock returns following large one-day declines: Evidence on short-term reversals and longer-term performance, Journal of Finance 49, 255-267.

Das, Sommath, Carolyn B. Levine, and K. Sivaramakrishnan, 1998, Earnings predictability and bias in analysts' earnings forecasts, Accounting Review 73, 277-294.

De Bondt, Werner F., and Richard H. Thaler, 1985, Does the stock market overreact?, Journal of Finance 40, 793-808.

De Bondt, Werner F., and Richard H. Thaler, 1987, Further evidence on investor overreaction and stock market seasonality, Journal of Finance 42, 557-581.

De Bondt, Werner F., and Richard H. Thaler, 1990, Stock market volatility: Do security analysts overreact?, American Economic Review 80, 52-57.

Dechow, Patricia M., Amy P. Hutton, and Richard G. Sloan, 2000, The relation between analysts' forecasts of long-term earnings growth and stock price performance following equity offerings, Contemporary Accounting Research 17, 1-32.

Dechow, Patricia M., and Richard G. Sloan, 1997, Returns to contrarian investment strategies: Tests of naïve expectations hypotheses, Journal of Financial Economics 43, 3-27.

Dissanaike, Gishan, 1994, On the computation of returns in tests of the stock market overreaction hypothesis, Journal of Banking & Finance 18, 1083-1094.

Dissanaike, Gishan, 1997, Do stock market investors overreact?, Journal of Business Finance & Accounting 24, 27-49.

Easterwood, John C., and Stacey R. Nutt, 1999, Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism?, Journal of Finance 54, 1777-1797.

Easton, Peter D., and Mark E. Zmijewski, 1989, Cross-sectional variation in the stock market response to accounting earnings announcements, Journal of Accounting and Economics 11, 117-141.

Einhorn, Hillel J., and Robin M. Hogarth, 1985, Ambiguity and uncertainty in probabilistic inference, Psychological Review 92, 433-461.

Elliott, John A., Donna R. Philbrick, and Christine I. Wiedman, 1995, Evidence from archival data on the relation between security analysts' forecast errors and prior forecast revisions, Contemporary Accounting Research 11, 919-938.

Elton, Edwin J., Martin J. Gruber, and Mustafa N. Gultekin, 1984, Professional expectations: Accuracy and diagnosis of errors, Journal of Financial and Quantitative Analysis 19, 351-363.

Ely, Kirsten M., and Vivek Mande, 1996, The interdependent use of earnings and dividends in financial analysts' earnings forecasts, Contemporary Accounting Research 13, 435-456.

Fama, Eugene F., 1973, A note on the market model and the two-parameter model, Journal of Finance 28, 1181-1185.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, Journal of Finance 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in returns on stocks and bonds, Journal of Financial Economics 33, 3-56.

Fama, Eugene F., and Kenneth R. French, 1995, Size and book-to-market factors in earnings and returns, Journal of Finance 50, 131-155.

Fama, Eugene F., and James D. Macbeth, 1973, Risk, return, and equilibrium: Empirical tests, Journal of Political Economy 81, 607-636.

Fama, Eugene F., 1998, Market efficiency, long-term returns, and behavioral finance, Journal of Financial Economics 49, 283-306.

Francis, Jennifer, and Donna Philbrick, 1993, Analysts' decisions as products of a multi-task environment, Journal of Accounting Research 31, 216-230

Givoly, Dan, and Josef Lakonishok, 1979, The information content of financial analysts' forecasts of earnings: Some evidence on semi-strong inefficiency, Journal of Accounting and Economics 1, 165-185.

Givoly, Dan, and Josef Lakonishok, 1980, Financial analysts' forecasts of earnings: Their value to investors, Journal of Banking and Finance 4, 221-233.

Gujarati, Damodar N., 1988, "Basic econometrics," Second Edition, McGraw-Hill Book Company, New York.

Hawkins, Eugene H., Stanley C. Chamberlin, and Wayne E. Daniel, 1984, Earnings expectations and security prices, Financial Analysts Journal 40, 24-38.

Hershleifer, Kent D., and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, Journal of Finance 53, 1839-1885.

Hogarth, Robin M., and Hillel J. Einhorn, 1992, Order effects in belief updating: The belief-adjustment model, Cognitive Psychology 24, 1-55.

Hughes, John S., and William E. Ricks, 1987, Associations between forecast errors and excess returns near to earnings announcements, Accounting Review 42, 158-175.

Jones, Steven L., 1993, Another look at time-varying risk and return in a long-horizon contrarian strategy, Journal of Financial Economics 33, 119-144.

Kahneman, Daniel, and Amos Tversky, 1972, Subjective probability: A judgment of representativeness, Cognitive Psychology 3, 430-454.

Kahneman, Daniel, and Amos Tversky, 1973, On the psychology of prediction, Psychological Review 80, 237-251.

Ketcher, David N., and Bradford D. Jordan, 1994, Short-term price reversals following major price innovations: Additional evidence on market overreaction, Journal of Economics and Business 46, 307-323.

Kim, Myung Jig, Charles R. Nelson, and Richard Startz, 1991, Mean reversion in stock prices? A reappraisal of the empirical evidence, Review of Economic Studies 58, 515-528.

Kothari, S. P., and Richard G. Sloan, 1992, Information in prices about future earnings: Implications for earnings response coefficients, Journal of Accounting and Economics 15, 143-171.

Kothari, S. P., and Jerold Zimmerman, 1995, Price and return models, Journal of Accounting and Economics 20, 155-192.

Kross, William, and Douglas Schroeder, 1988, Firm prominence and the differential information content of quarterly earnings announcements, Journal of Business Finance & Accounting 16, 55-74.

Kross, William, Byung Ro, and Douglas Schroeder, 1990, Earnings expectations: Analysts' information advantage, Accounting Review 65, 461-476.

La Porta, Rafael, 1996, Expectations and the cross-section of stock returns, Journal of Finance 51, 1715-1742.

Lim, Terence, 2001, Rationality and Analysts' Forecast Bias, Journal of Finance 56, 369-385.

Lys, Thomas, and Sungkyu Sohn, 1990, The association between revisions of financial analysts' earnings forecasts and security-price changes, Journal of Accounting and Economics 13, 341-363.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, Journal of Finance 49, 1541-1578.

Mendenhall, R., 1991, Evidence of the possible underweighting of earnings-related information, Journal of Accounting Research 29, 170-180.

Michaely, Roni, and Kent Womack, 1999, Conflict of interest and the credibility of underwriter analyst recommendations, Review of Financial Studies 12, 653-686.

Michaely, Roni, Richard H. Thaler, and Kent Womack, 1995, Price reactions to dividend initiations and omissions: Overreaction or drift?, Journal of Finance 50, 573-608.

Mitchell, Mark L., and Erik Stafford, 2000, Managerial decisions and long-term stock price performance, Journal of Business 73, 287-329.

Moses, O. Douglas, 1991, Cash flow signals and analysts' earnings forecast revisions, Journal of Business Finance & Accounting 18, 807-832.

O'Brien, Patricia C., 1988, Analysts' forecasts as earnings expectations, Journal of Accounting and Economics 10, 53-83.

Philbrick, Donna R., and William E. Ricks, 1991, Using Value Line and I/B/E/S analyst forecasts in accounting research, Journal of Accounting Research 29, 397-417.

Scharfstein, David S., and Jeremy C. Stein, 1990, Herd behavior and investment, American Economic Review 80, 465-479.

Seyhun, H. N., 1990, Overreaction or fundamentals: Some lessons from insiders' response to the market crash of 1987, Journal of Finance 45, 1363-1388.

Shefrin, Hersh, 2000, "Beyond greed and fear: Understanding behavioral finance and the psychology of investing," Harvard Business School Press, Boston, Massachusetts.

Stickel, Scott E., Common stock returns surrounding earnings forecast revisions: More puzzling evidence, Accounting Review 66, 402-416.

Teets, Walter, 1992, The association between stock market response to earnings announcements and regulation of electric utilities, Journal of Accounting Research 30, 274-285.

Thaler, Richard H., 1986, The Psychology and economic conference handbook: Comments on Simon, on Einhorn and Hogarth, and on Tversky and Kahneman, Journal of Business 59, S279-S284.

Tversky, Amos, and Daniel Kahneman, 1973, Availability: A heuristic for judging frequency and probability, Cognitive Psychology 5, 207-232.

Watts, Ross L., 1978, Systematic 'abnormal' returns after quarterly earnings announcements, Journal of Financial Economics 6, 127-150.

Womack, Kent L., 1996, Do brokerage analysts' recommendations have investment value?, Journal of Finance 51, 137-167.

Zarowin, Paul, 1989, Short-run market overreaction: Size and seasonality effects, Journal of Portfolio Management 15, 26-29.

Zarowin, Paul, 1990, Size, seasonality, and stock market overreaction, Journal of Financial and Quantitative Analysis 25, 113-125.

APPENDIX

Figures and Tables Discussed in Text

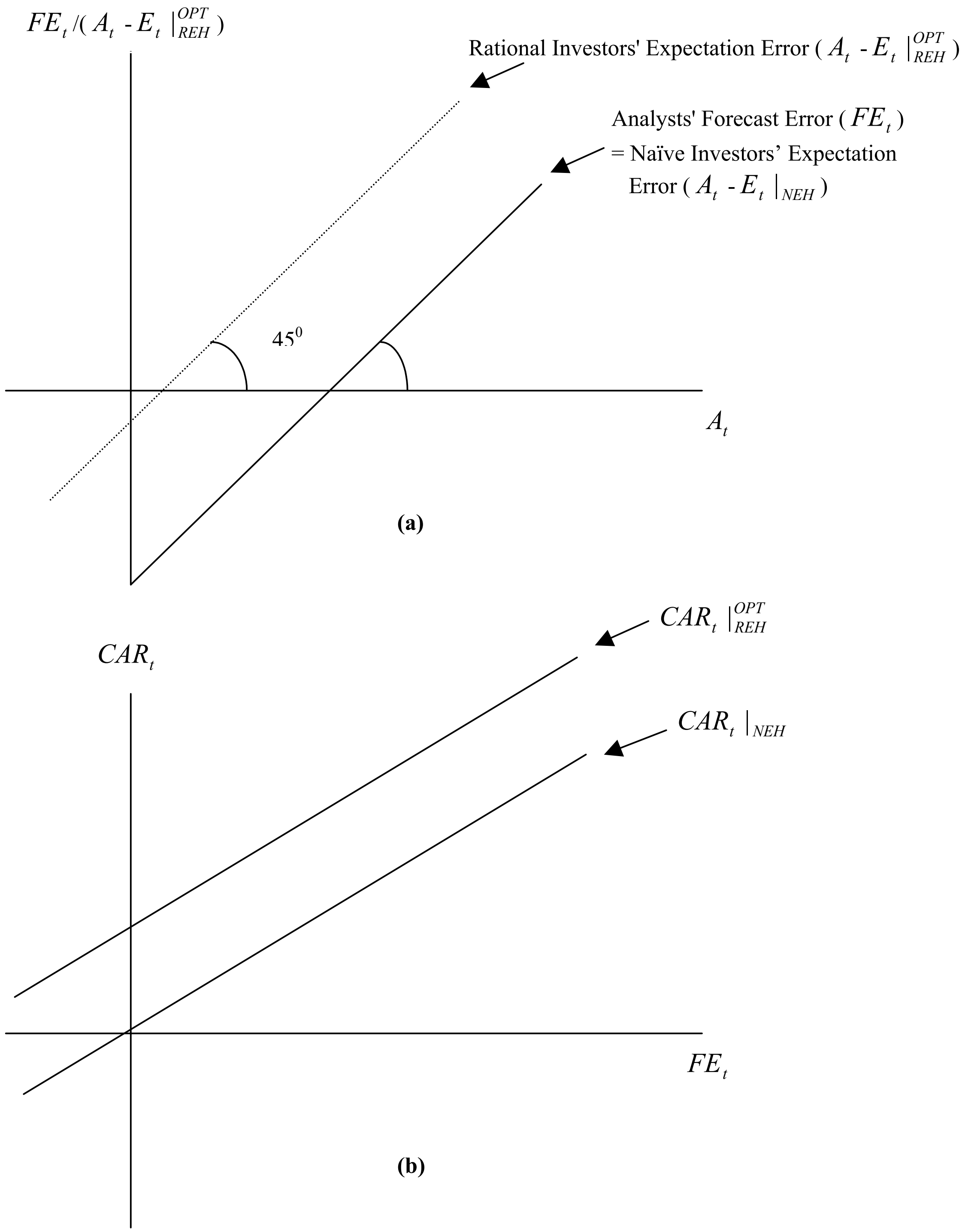

Figure 1. Investors' Earnings Expectations and Reaction to Analysts' Optimism Under the Rational Expectations Hypothesis (REH)

Table 1. Analysts' Earnings Forecasts versus Investors' Earnings Expectations and Predicted Cumulative Abnormal Returns (CARs)

	Hypothesis	
Portfolio	***Naïve Expectations Hypothesis (NEH)***	***Rational Expectations Hypothesis (REH)***
Optimistic Portfolio	$E_t\|_{NEH}^{OPT} = F_t$ $\rightarrow A_t - E_t\|_{NEH}^{OPT} = A_t - F_t$ $\rightarrow CAR_t\|_{NEH}^{OPT} = CAR_t\|_{NEH}$	$E_t\|_{REH}^{OPT} < F_t$ $\rightarrow A_t - E_t\|_{REH}^{OPT} > A_t - F_t$ $\rightarrow CAR_t\|_{REH}^{OPT} > CAR_t\|_{NEH}$
Rational Portfolio	$E_t\|_{NEH}^{RAT} = F_t$ $\rightarrow A_t - E_t\|_{NEH}^{RAT} = A_t - F_t$ $\rightarrow CAR_t\|_{NEH}^{RAT} = CAR_t\|_{NEH}$	$E_t\|_{REH}^{RAT} = F_t$ $\rightarrow A_t - E_t\|_{REH}^{RAT} = A_t - F_t$ $\rightarrow CAR_t\|_{REH}^{RAT} = CAR_t\|_{NEH}$
Pessimistic Portfolio	$E_t\|_{NEH}^{PESS} = F_t$ $\rightarrow A_t - E_t\|_{NEH}^{PESS} = A_t - F_t$ $\rightarrow CAR_t\|_{NEH}^{PESS} = CAR_t\|_{NEH}$	$E_t\|_{REH}^{PESS} > F_t$ $\rightarrow A_t - E_t\|_{REH}^{PESS} < A_t - F_t$ $\rightarrow CAR_t\|_{REH}^{PESS} < CAR_t\|_{NEH}$

Note that firm subscripts are omitted.

Definitions of variables are as follows:

$E_t|_{HYP}^{BIAS}$ = naïve or rational (*HYP*) investors' earnings expectations for quarter *t* in response to analysts' *BIAS* [=optimism (*OPT*), rational forecasts (*RAT*), or pessimism (*PESS*)] in consensus earnings forecasts under *HYP* (=*NEH* or *REH*);

F_t = analysts' consensus earnings forecasts for quarter *t*;

$A_t - E_t|_{HYP}^{BIAS}$ = investors' expectation errors for quarter *t* under *HYP* in response to analysts' *BIAS*;

$A_t - F_t$ = analysts' forecast errors for quarter *t* (FE_t);

$CAR_t|_{NEH}$ = naïve investors' reaction to analysts' forecast errors manifested in 3-day [-2: 0] cumulative abnormal returns (*CAR*s) for quarter *t*; and

$CAR_t|_{HYP}^{BIAS}$ = naïve or rational (*HYP*) investors' reaction to analysts' *BIAS* in consensus earnings forecasts.

Table 2. Portfolio Formation: Mean-Frequency Forecast Error (MFFE) versus Mean-Frequency Time-Series (MFTS) Methods

I use two statistical methods to form the desired portfolios on the basis of analysts' forecasting behavior over the past 20 quarters (i.e., 5 years). Panel A summarizes the *MFFE* method using the mean and frequency of analysts' forecast errors over 5 years prior to the quarterly earnings announcement. Each firm quarter is assigned into one of the quintile portfolios at each earnings announcement based on the past 5-year mean and frequency. The mean of quarterly forecast errors (*MQFEs*) over the 5-year period is calculated as follows:

$$MQFE_{t,20} = \frac{1}{20}\sum_{q=1}^{20}\frac{A_{t-q} - F_{t-q}}{P_{t-q-1}}$$

where

q = 1 through 20 quarters prior to the quarterly announcement at time t;

A_{t-q} = the actual *EPS* for the quarter *t-q*;

F_{t-q} = the forecasted *EPS* at one month prior to the quarter *t-q*; and

P_{t-q} = the stock price 25 days prior to the quarter *t-q*.

The frequency of quarterly forecast errors indicates the number of negative forecast errors over the 5-year period. The larger the number is the more optimistic the contemporaneous forecast error would be. Both measures – i.e., *MQFE* and the frequency – rank firm-quarters into quintiles resulting in 25 subsets when a contingency table is constructed. Then, the subsets are redefined into 5 portfolios as in Panel A.

Panel B presents portfolio formation using the time-series regression model developed by De Bondt and Thaler (*DBT*; 1990):

$$A_t - A_{t-1} = \delta_0 + \delta_1(F_t - A_{t-1}) + e'_t$$
$$\Leftrightarrow AEC_t = \delta_0 + \delta_1(FEC_t) + e'_t$$

where

A_t = the contemporaneous reported earnings at quarter t;

F_t = the analysts' consensus earnings forecast for quarter t;

A_{t-1} = the reported earnings one quarter prior to quarter t;

$AEC_t = A_t - A_{t-1}$ = actual earnings change; and

$FEC_t = F_t - A_{t-1}$ = forecasted earnings change;

Recall that the firm subscript is omitted.

Note that both methods form 5 portfolios on the basis of analysts' past forecasting behavior. The Mean-Frequency Time-Series (*MFTS*) method is a combination of the *MFFE* and the *DBT*.

Table 2. Continued.

Panel A. Mean-Frequency Forecast Error (MFFE) Method					
	MQFE Rank				
Frequency Rank (No of (-) FE)	***Q1***	***Q2***	***Q3***	***Q4***	***Q5***
Q1	**P1** (4980, 580)	**P1** (3164, 499)	**P2** (1264, 250)	(84, 51)	(165, 46)
Q2	**P1** (2113, 506)	**P2** (2573, 625)	**P3** (2229, 522)	(644, 241)	(563, 157)
Q3	**P2** (1266, 359)	**P3** (2043, 554)	**P3** (2807, 697)	**P4** (1757, 524)	**P4** (1573, 391)
Q4	(557, 181)	(945, 316)	(2008, 554)	**P4** (2664, 617)	**P5** (2510, 556)
Q5	(217, 67)	(408, 133)	(825, 281)	**P5** (3984, 555)	**P5** (4322, 630)

Note that the numbers in parentheses indicate firm-quarters and firms respectively.

For both measures (*MQFE* and Frequency), lower ranks (e.g., Q1) represent more optimism in analysts' forecasts during the past 5-year period prior to the earnings announcement. Conversely, higher ranks (e.g., Q5) indicate less optimism or more pessimism in analysts' forecasts. Based on the newly formed subsets, I create 5 portfolios ranging from the most optimistic (P1) to the most pessimistic (P5).

Table 2. Continued.

Panel B. Portfolio Characteristics*		
Portfolio	***Expected Sign of AMQFE [a] and AFE [b] (firm-quarters, firms)***	***Analysts' Behavior***
Portfolio 1 (P1)	Most Negative (8512, 909)	Most Optimistic
Portfolio 2 (P2)	Negative (4482, 978)	Optimistic ?[c]
Portfolio 3 (P3)	Negative (6441, 1051)	Optimistic ?[c]
Portfolio 4 (P4)	Positive (5340, 907)	Pessimistic
Portfolio 5 (P5)	More Positive (9830, 1053)	Most pessimistic

* Portfolio definitions are consistent throughout the dissertation.

[a] *AMQFE* indicates average *MQFE*, which is the grand mean of *MQFE* for each portfolio:

$$AMQFE_P = \frac{1}{N}\sum_{n=1}^{N} MQFE_{P,n}$$

where N = the number of observations (*MQFEs*) in the portfolio P (P=1,2,…,5).

[b] *AFE* indicates average contemporaneous analysts' forecast errors.

[c] As discussed in the text, the classification of these two portfolios may be controversial (They might be seen as either rational or pessimistic).

Table 2. Continued.

Panel C. Time-Series Portfolio Formation Method (De Bondt & Thaler)* $A_t - A_{t-1} = \delta_0 + \delta_1 (F_t - A_{t-1}) + e'_t$						
		Rank of δ_0				
		1	***2***	***3***	***4***	***5***
Rank of δ_1	***1***	**P1** (1586, 292)	**P1** (1884, 427)	**P2** (1784, 411)	**P3** (2090, 452)	(1605, 327)
	2	**P1** (1711, 382)	**P2** (1892, 516)	**P3** (1904, 511)	(1844, 528)	(1598, 412)
	3	**P2** (1176, 336)	**P3** (1624, 451)	(2250, 522)	(2027, 513)	**P4** (1872, 434)
	4	**P3** (1921, 382)	(1752, 464)	(1682, 456)	**P4** (1634, 477)	**P5** (1960, 450)
	5	(2555, 383)	(1797, 406)	**P4** (1329, 373)	**P5** (1354, 365)	**P5** (1914, 337)

* The time-series model is estimated over the last 5 years (i.e., 20 quarters) at each earnings announcement. Negative intercepts ($\delta_0 s$) likely indicate more optimism in analysts' forecasts resulting in negative forecast errors, holding the slope coefficient (δ_1) constant. Holding δ_0 constant, slopes less than one and greater than zero more likely lead to analysts' pessimism. The ranks of δ_0 and δ_1, thus, indicate the degree of either analysts' optimism or pessimism. Specifically, I rank alphas and betas in quintiles and obtain the above table that has possible combinations of $\delta_0 s$ and $\delta_1 s$ quintiles. For both measures, lower ranks represent more optimism in analysts' forecasts during the past 5-year period prior to the earnings announcement. Conversely, higher ranks indicate less optimism or more pessimism in analysts' forecasts.[60] Based on the newly formed subsets, I again create 5 portfolios (P1, …, P5).

[60] Note that observations with negative slope coefficients ($\delta_1 s$) are dropped for simplicity and clarification purposes. This should not affect the validity of the classification because $\delta_1 s$ are, in most cases, greater than zero.

Table 2. Continued.

Now, I have 5 portfolios from the *MFFE* method and 5 portfolios from the *DBT* model. The following *MFTS* method reconciles the two formation methods and forms another 5 portfolios. Each portfolio in the *MFTS* contains observations that are classified into the same portfolio by both the *MFFE* and the *DBT* methods. The following table summarizes the *MFTS* formation process:

Panel D. Mean-Frequency Time-Series (MFTS) Method					
	MFFE				
DBT	***P1***	***P2***	***P3***	***P4***	***P5***
P1	**P1** (2965, 470)	(721, 271)	(286, 121)	(10, 7)	(10, 4)
P2	(1446, 420)	**P2** (891, 373)	(1022, 350)	(210, 60)	(56, 19)
P3	(1524, 388)	(903, 357)	**P3** (1510, 476)	(758, 270)	(776, 207)
P4	(9, 9)	(62, 36)	(493, 189)	**P4** (996, 361)	(1962, 489)
P5	(1, 1)	(14, 11)	(100, 55)	(1030, 281)	**P5** (2635, 492)

Table 3. Descriptive Statistics

This table displays descriptive statistics, including mean, median, and frequency, of variables used for empirical tests. Definitions of variables are as follows:

ACAR = the average cumulative abnormal return

$= \frac{1}{N}\sum_{n=1}^{N} CAR_n$ where CAR is the 3-day [–2: 0] abnormal stock return for a quarterly earnings announcement;

AMQFE $= \frac{1}{N}\sum_{n=1}^{N} MQFE_n$ (the average of *MQFE*)

where $MQFE_{t,20} = \frac{1}{20}\sum_{q=1}^{20} \frac{A_{t-q} - F_{t-q}}{P_{t-q-1}}$;

AFE = the average of analysts' earnings forecast errors (*FE*);

Asize = the average of market value of equity (MVE =*Size*) in millions

$= \sum_{n=1}^{N} (P \times Shr)_{t,n} / N$

where P is the closing stock price at the third month of quarter *t*, *Shr* is the number of common shares used to calculate EPS at quarter *t*, and *N* is the number of observations;

AlogSize = the average of the logarithm of MVE ;

ABtoM = the average of book-to-market ratio

$= \sum_{n=1}^{N} \frac{BVE_n}{MVE_n} / N$ where BVE = *COMPUSTAT* common equity (total);

 # analysts = the average number of analysts for each portfolio;

(+)% FE = the percentage of positive analysts' forecast errors for each portfolio;

(–)% FE = the percentage of negative analysts' forecast errors for each portfolio; and

STD = the portfolio mean of the standard deviation of analysts' consensus forecasts standardized by the mean consensus forecasts.

Other terms are as defined in text. Note that subscripts *T* and *P* are omitted.

Table 3. Continued.

Panel A. Mean-Frequency Forecast Error (MFFE) Method: Overall Mean, Median, Frequency of CAR, MQFE, FE, Size, logSize, and BtoM						
	N	***Mean***	***Median***	***(+) Frequency***	***(–) Frequency***	***zero Frequency***
CAR	34605	0.00334***	0.00124			
MQFE	34605	-0.00138***	-0.00008	15544 (44.92%)	19061 (55.08%)	0
FE	34605	-0.00048***	0	17185 (49.66%)	13173 (38.07%)	4247 (12.27%)
Size	34605	4443.773	909.951			
logSize	34605	6.887439	6.81339			
BtoM	34605	0.534931	0.47271			

*** significant at the 1% level.
** significant at the 5% level.
* significant at the 10% level.

Panel B. MFFE: Means of CAR, MQFE, FE, Size, logSize, and BtoM over Time							
	N	***$ACAR_T$***	***$AMQFE_T$***	***AFE_T***	***$Asize_T$***	***$AlogSize_T$***	***$ABtoM_T$***
1990	1686	-0.00068	-0.00208***	-0.00142***	3103.00	6.9026	0.6648
1991	2057	-0.00068	-0.00200***	-0.00102***	2968.89	6.8302	0.6470
1992	2480	0.00593***	-0.00201***	-0.00067***	3001.85	6.7745	0.5902
1993	2702	0.00245***	-0.00205***	-0.00059***	3072.00	6.7831	0.5215
1994	3084	0.00256***	-0.00193***	-0.00029***	2927.98	6.7079	0.5187
1995	3199	0.00114	-0.00189***	-0.00064***	3245.01	6.7276	0.5137
1996	3426	0.00429***	-0.00154***	-0.00055***	3957.39	6.8688	0.5006
1997	3589	0.00200***	-0.00116***	-0.00017**	4780.93	7.0425	0.4585
1998	3650	0.00459***	-0.00069***	-0.00041***	5588.20	7.0617	0.4650
1999	3706	0.00849***	-0.00068***	-0.00007	5559.75	6.8851	0.5343
2000	3389	0.00526***	-0.00065***	-0.00007	6899.85	6.9262	0.5877
2001	1371	-0.00146	-0.00049***	-0.00063***	8148.44	7.1466	0.5603

Table 3. Continued.

Panel C. MFFE: Descriptive Statistics of CAR, MQFE, FE, # of Analysts, STD, Size, logSize, and BtoM across Portfolios

	N	*ACAR$_P$*	*AMQFE$_P$*	*AFE$_P$*	*median FE*	*%(+FE)*	*%(–FE)*
P1	8512	0.00352***	-0.00542***	-0.00171***	0.00000	0.47	0.53
P2	4482	0.00427***	-0.00203***	-0.00057***	0.00000	0.52	0.48
P3	6441	0.00395***	-0.00036***	-0.00037***	0.00000	0.54	0.46
P4	5340	0.00305***	0.00041***	0.00014***	0.00008	0.60	0.40
P5	9830	0.00251***	0.00076***	0.00023***	0.00016	0.67	0.33

	N	*# Analysts*	*Asize$_P$*	*AlogSize$_P$*	*ABtoM$_P$*	*STD*
P1	8512	5.01	1315.58	5.9578	0.6905	0.32
P2	4482	6.59	2375.62	6.5209	0.5913	0.22
P3	6441	7.88	4230.72	7.0527	0.4903	0.12
P4	5340	8.35	5794.30	7.3901	0.4672	0.11
P5	9830	8.84	7501.46	7.4782	0.4406	0.09

Note: P1 denotes the most optimistic portfolio; P2 denotes another optimistic portfolio – i.e., less optimistic than P1 and more optimistic than P3; P3 denotes the least optimistic portfolio – i.e., less optimistic than both P1 and P2; P4 denotes a less pessimistic portfolio than P5; P5 denotes the most pessimistic portfolio.

Panel D. Mean-Frequency Time-Series (MFTS) Method: Overall Mean, Median, Frequency of CAR, MQFE, FE, Size, logSize, and BtoM

	N	*Mean*	*Median*	*(+) Frequency*	*(–) Frequency*	*zero Frequency*
CAR	8997	0.00350***	0.00150			
MQFE	8997	-0.00179***	-0.00021	3737 (41.54%)	5260 (58.46%)	0
FE	8997	-0.00066***	0.00003	4517 (50.2%)	3567 (39.65%)	913 (10.15%)
Size	8997	3828.20	795.92			
logSize	8997	6.76892	6.6795			
BtoM	8997	0.56547	0.5655			

Table 3. Continued.

Panel E. MFTS: Means of CAR, MQFE, FE, Size, logSize, and BtoM over Time							
	N	*$ACAR_T$*	*$AMQFE_T$*	*AFE_T*	*$Asize_T$*	*$AlogSize_T$*	*$ABtoM_T$*
1990	381	-0.00016	-0.00234***	-0.00208***	2924.38	6.8192	0.6995
1991	507	-0.00138	-0.00234***	-0.00117***	2569.44	6.7475	0.6570
1992	685	0.00791***	-0.00291***	-0.00069***	2588.51	6.5850	0.6139
1993	663	0.00318*	-0.00315***	-0.00105***	2788.11	6.5293	0.5567
1994	760	0.00304*	-0.00263***	-0.00062***	2388.75	6.5802	0.5343
1995	890	0.00298*	-0.00247***	-0.00080***	3992.58	6.7335	0.5273
1996	944	0.00459***	-0.00195***	-0.00070***	4274.88	6.8463	0.5135
1997	964	0.00278*	-0.00148***	-0.00012	3606.87	6.8125	0.4910
1998	969	0.00333**	-0.00081***	-0.00075***	4597.63	6.9342	0.5161
1999	954	0.00699***	-0.00085***	-0.00028	4559.57	6.8049	0.5850
2000	886	0.00196	-0.00074***	-0.00018	5223.82	6.8960	0.6349
2001	392	0.00282	-0.00069***	-0.00068*	5327.04	6.8483	0.6192

Panel F. MFTS: Descriptive Statistics of CAR, MQFE, FE, # of Analysts, STD, Size, logSize, and BtoM across Portfolios							
	N	*$ACAR_P$*	*$AMQFE_P$*	*AFE_P*	*median FE*	*%(+FE)*	*%(–FE)*
P1	2965	0.00381***	-0.00573***	-0.00207***	-0.00015	0.45	0.55
P2	891	0.00398**	-0.00161***	-0.00054**	0.00000	0.51	0.49
P3	1510	0.00448***	-0.00034***	-0.00025**	0.00000	0.55	0.45
P4	996	0.00184	0.00033***	0.00013	0.00014	0.61	0.39
P5	2635	0.00306***	0.00094***	0.00035***	0.00033	0.69	0.31

	N	*# Analysts*	*$Asize_P$*	*$AlogSize_P$*	*$ABtoM_P$*	*STD*
P1	2965	4.34	1356.08	5.8541	0.6933	0.334
P2	891	5.70	2151.47	6.2760	0.6049	0.204
P3	1510	7.80	4690.14	7.1434	0.4709	0.096
P4	996	8.48	4456.69	7.4315	0.4959	0.105
P5	2635	9.28	6445.39	7.4999	0.4888	0.130

Table 4. Validity Test for MFFE and MFTS: Binomial Test

This table summarizes a binomial test of the null hypothesis that the probability (p) of getting positive forecast errors [*(+) FEs*] is 0.5 for all *n* trials – i.e., Ho: $p = 1/2$. Note that "*n*" is the total number of positive and negative *FE*s excluding zero *FE*s. Following Conover (1980; pp. 96-99), I calculate the test statistic (*T*) and the corresponding critical regions at the 5% and 1% levels as follows:

T = the number of *(+) FEs*;

t1_5% (lower limit at the 5% level) = $np - 1.96\sqrt{np(1-p)}$;

t2_5% (upper limit at the 5% level) = $np + 1.96\sqrt{np(1-p)}$;

t1_1% (lower limit at the 1% level) = $np - 2.58\sqrt{np(1-p)}$;

t2_1% (upper limit at the 1% level) = $np + 2.58\sqrt{np(1-p)}$.

Panel A. MFFE

	N	*# (+)FE*	*# (–)FE*	*n*	*% (+)FE*	*% (–)FE*	*T*	*t1_1%*	*t2_1%*	*t1_5%*	*t2_5%*
P1*	8512	3634	4134	7768	47	53	3634	3770	3998	3798	3970
P2*	4482	2108	1912	4020	52	48	2108	1928	2092	1948	2072
P3*	6441	3013	2549	5562	54	46	3013	2685	2877	2708	2854
P4*	5340	2831	1860	4691	60	40	2831	2257	2434	2278	2413
P5*	9830	5599	2718	8317	67	33	5599	4041	4276	4069	4248
Total	34605										

Panel B. MFTS

	N[a]	*# (+)FE*	*# (–)FE*	*N*[a]	*% (+)FE*	*% (–)FE*	*T*	*t1_1%*	*t2_1%*	*t1_5%*	*t2_5%*
P1*	2965	1209	1505	2714	45	55	1209	1290	1424	1306	1408
P2	891	409	397	806	51	49	409	366	440	375	431
P3*	1510	724	584	1308	55	45	724	607	701	619	689
P4*	996	549	344	893	61	39	549	408	485	417	476
P5*	2635	1626	737	2363	69	31	1626	1119	1244	1134	1229
Total	8997										

[a] *N* includes the number of zero *FE*s, while *n* does not.
*** significant at the 1% level.
** significant at the 5% level.
* significant at the 10% level.

Note 1: *N* is the total number of observations in each portfolio; *#(+)FE* is the number of positive forecast errors; *#(–)FE* is the number of negative forecast errors; *n* is the number of *#(+)FE* plus *#(–)FE*. Other terms are as defined above.

Note 2: P1 denotes the most optimistic portfolio; P2 denotes another optimistic portfolio – i.e., less optimistic than P1 and more optimistic than P3; P3 denotes the least optimistic portfolio – i.e., less optimistic than both P1 and P2; P4 denotes a less pessimistic portfolio than P5; P5 denotes the most pessimistic portfolio.

Table 5. Persistent Bias in Analysts' Earnings Forecasts: Autocorrelation Test

Panel A shows a nonparametric Chi-square test to test the null hypothesis that getting (+) *FE* at the contemporaneous quarter is equally likely as getting (−) *FE*. Each subset contains the number of *FE* sign transitions (including no sign transitions) that firms make from quarter *t-1* to the contemporaneous quarter *t*. There are four subsets in this case because I compare contemporaneous *FE* (FE_t) with *FE* one quarter prior to the contemporaneous one (FE_{t-1}). The test statistic (Chi-square; χ^2) and theoretical frequencies are calculated as follows:[61]

$$\chi^2 = \sum_{d=1}^{4} \frac{(O_d - T_d)^2}{T_d} \text{ with } df = (r-1)(c-1)$$

where

O_d = the observed frequency of *FE* sign transitions for subset *d* where *d* = 1,…,4;

T_d = the theoretical frequency of *FE* sign transitions for subset *d* under the null hypothesis;

df = degree of freedom for the χ^2 test;

r = the number of rows in the contingency table (2 in this case); and

c = the number of columns in the contingency table (2 in this case).

Panel B summarizes the results from a parametric test of autocorrelation between FE_t and FE_{t-1}. The following are the specification of the first-order autoregressive [AR(1)] models used to test the autocorrelation structure of *FE*s:

$$SFE_t = \lambda_0 + \lambda_1 SFE_{t-1} + \varpi_t$$

$$SFE_t = \lambda_0' + \lambda_1' SFE_{t-1} + \lambda_2' SFE_{t-1} D2 + \lambda_3' SFE_{t-1} D3 + \lambda_4' SFE_{t-1} D4 + \lambda_5' SFE_{t-1} D5 + \varpi_t'$$

where

SFE_t = the analysts' forecast errors (FE_t) standardized by the stock price 10 days prior to the earnings announcement at *t*;

SFE_{t-1} = the lagged analysts' forecast errors (FE_{t-1}) standardized by the stock price 10 days prior to the earnings announcement at *t-1*;

$D2$ = a dummy variable that equals one if an observation belongs to P2 and zero otherwise;

$D3$ = a dummy variable that equals one if an observation belongs to P3 and zero otherwise;

$D4$ = a dummy variable that equals one if an observation belongs to P4 and zero otherwise;

$D5$ = a dummy variable that equals one if an observation belongs to P5 and zero otherwise; and

ϖ_t, ϖ_t' = independently and identically distributed random error terms.

Again firm subscripts are omitted.

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[61] Refer to Gujarati (1988; pp. 373-375). The theoretical frequency is computed by multiplying the marginal frequency of the contemporaneous forecast errors (i.e., *# of (+)* or *(-) FE* at *t*) by the ratio of the marginal frequency of the lagged forecast errors (i.e., *# of (+)* or *(-) FE* at *t-1*) over the total frequency (=27255). For example, the theoretical frequency of 8702 is calculated as follows: 15246 × (15557 ÷ 27255).

Table 5. Continued.

Panel A. Non-Parametric Chi-square Test: MFFE					
	Observed			***Theoretical***	
	# of (+) FE at t	***# of (–) FE at t***	***Total***	***# of (+) FE at t***	***# of (–) FE at t***
# of (+) FE at t-1	10627	4930	*15557*	8702	6855
# of (–) FE at t-1	4619	7079	*11698*	6544	5154
	15246	*12009*	*27255*	*15246*	*12009*

$$\chi^2 = 2251$$
$$df = 1$$
$$\chi^2(1) = 3.83\ (5\%)\ \text{or}\ 6.63\ (1\%)$$

Panel B. Non-Parametric Chi-square Test: MFTS					
	Observed			***Theoretical***	
	# of (+) FE at t	***# of (–) FE at t***	***Total***	***# of (+) FE at t***	***# of (–) FE at t***
# of (+) FE at t-1	2846	1331	*4177*	2297	1880
# of (–) FE at t-1	1228	2005	*3233*	1777	1456
	4074	*3336*	*7410*	*4074*	*3336*

$$\chi^2 = 669$$
$$df = 1$$
$$\chi^2(1) = 3.83\ (5\%)\ \text{or}\ 6.63\ (1\%)$$

Panel C. Parametric Test: First-Order Autoregressive Model [AR(1)] without Portfolio Dummies

$$SFE_t = \lambda_0 + \lambda_1 SFE_{t-1} + \varpi_t$$

	Mean-Frequency Forecast Error (MFFE) Method		***Mean-Frequency Time-Series (MFTS) Method***	
Coefficient	***Estimate***	*Pr > |t|*	***Estimate***	***Pr > |t|***
λ_0	-0.00041	<.0001	-0.00054	<.0001
λ_1	0.08370	<.0001	0.09390	<.0001
R-square	0.0229		0.0249	

Table 5. Continued.

Panel D. Parametric Test: AR(1) with Portfolio Dummies $SFE_t = \lambda_0' + \lambda_1' SFE_{t-1} + \lambda_2' SFE_{t-1}D2 + \lambda_3' SFE_{t-1}D3 + \lambda_4' SFE_{t-1}D4 + \lambda_5' SFE_{t-1}D5 + \varpi_t$				
	Mean-Frequency Forecast Error (MFFE) Method		***Mean-Frequency Time-Series (MFTS) Method***	
Coefficient	***Estimate***	*Pr* > |*t*|	***Estimate***	***Pr* > |*t*|**
λ_0'	-0.00046	<.0001	-0.00056	<.0001
λ_1'	0.0740	<.0001	0.0933	<.0001
λ_2'	-0.0492	<.0001	-0.0683	0.0024
λ_3'	0.1298	<.0001	0.1450	0.0028
λ_4'	0.1100	<.0001	0.1059	0.0900
λ_5'	0.1708	<.0001	0.0303	0.1705
Marginal Effect				
λ_1' ***(P1)***	0.0740	<.0001	0.0933	<.0001
$\lambda_1' + \lambda_2'$ ***(P2)***	0.0248	0.0022	0.0250	0.2438
$\lambda_1' + \lambda_3'$ ***(P3)***	0.2038	<.0001	0.2383	<.0001
$\lambda_1' + \lambda_4'$ ***(P4)***	0.1840	<.0001	0.1992	0.0013
$\lambda_1' + \lambda_5'$ ***(P5)***	0.2448	<.0001	0.1236	<.0001
Pair-wise Comparison	***F-value***	***Pr* > |*F*|**	***F-value***	***Pr* > |*F*|**
$\lambda_1' = \lambda_1' + \lambda_2'$	31.59	<.0001	9.19	0.0024
$\lambda_1' = \lambda_1' + \lambda_3'$	39.78	<.0001	8.94	0.0028
$\lambda_1' = \lambda_1' + \lambda_4'$	56.87	<.0001	2.87	0.0900
$\lambda_1' = \lambda_1' + \lambda_5'$	155.63	<.0001	1.88	0.1705
$\lambda_1' + \lambda_2' = \lambda_1' + \lambda_3'$	67.06	<.0001	16.46	<.0001
$\lambda_1' + \lambda_2' = \lambda_1' + \lambda_4'$	94.99	<.0001	7.04	0.0080
$\lambda_1' + \lambda_2' = \lambda_1' + \lambda_5'$	200.48	<.0001	10.79	0.0010
$\lambda_1' + \lambda_3' = \lambda_1' + \lambda_4'$	0.64	0.4232	0.25	0.6177
$\lambda_1' + \lambda_3' = \lambda_1' + \lambda_5'$	2.85	0.0913	4.79	0.0287
$\lambda_1' + \lambda_4' = \lambda_1' + \lambda_5'$	9.86	0.0017	1.33	0.2480
R-square	0.0311		0.0275	

Table 6. Persistence Bias in Analysts' Earnings Forecasts: Herfindahl Index

This table shows portfolio-time frequencies, industry frequencies, stock exchange frequencies, and corresponding Herfindahl indexes – Time Herfindahl, Industry Herfindahl, and Stock Exchange Herfindahl. The portfolio-time frequencies are firm-quarters in each portfolio over time (12-year period), while the industry frequencies reflect firm-quarters in each portfolio across industry sectors. Herfindahl indexes in Panels A and B measure the relative concentration of a portfolio over the 12-year period and are calculated as follows:

$$H_P = \sum_{t=1}^{12} \frac{FREQ_{t,P}}{FREQ_{sum,P}}$$

where

H_P = the Herfindahl index for portfolio P where P = P1, …, P5;

$FREQ_{t,P}$ = the marginal frequency of portfolio P in year t; and

$FREQ_{sum,P}$ = the aggregate frequency of portfolio P over the 10-year period.

Portfolios, which are observed in a specific year, will have a Herfindahl index of "1". Portfolios, which are spread evenly over time, will have a Herfindahl index of "0.0833". Herfindahl indexes in Panels C and D (E and F) indicate the relative concentration of an industry sector (an exchange) across portfolios and are computed as follows:

$$H_{IND} = \sum_{p=1}^{5} \frac{FREQ_{p,IND}}{FREQ_{sum,IND}}$$

$$H_{EX} = \sum_{p=1}^{5} \frac{FREQ_{p,EX}}{FREQ_{sum,EX}}$$

where

H_{IND} = the Herfindahl index for industry sector IND where IND = 1, …, 11;

H_{EX} = the Herfindahl index for an exchange EX where EX = *NYSE*, *AMEX*, *NASDAQ*;

$FREQ_{p,IND}$ = the marginal frequency of an industry IND for a portfolio p;

$FREQ_{p,EX}$ = the marginal frequency of an exchange EX for a portfolio p;

$FREQ_{sum,IND}$ = the aggregate frequency of an industry IND across portfolios; and

$FREQ_{sum,EX}$ = the aggregate frequency of an exchange EX across portfolios.

If an industry sector (or an exchange) clusters in a specific portfolio, it will have a Herfindahl index of "1". If an industry sector (or an exchange) is evenly spread across portfolios, it will have a Herfindahl index of "0.2".

Table 6. Continued.

Panel A. Time Herfindahl Index: MFFE										
	Portfolio Frequency over Time					*Herfindahl Index for Each Portfolio across Years*				
Year	***P1***	***P2***	***P3***	***P4***	***P5***	***P1***	***P2***	***P3***	***P4***	***P5***
1990	551	267	392	250	226	0.0043	0.0036	0.0038	0.0022	0.0005
1991	672	308	446	360	271	0.0063	0.0048	0.0049	0.0046	0.0008
1992	808	420	520	387	345	0.0092	0.0089	0.0067	0.0053	0.0012
1993	963	403	545	386	405	0.0130	0.0082	0.0073	0.0053	0.0017
1994	1079	451	630	451	473	0.0164	0.0103	0.0098	0.0073	0.0023
1995	968	450	610	547	624	0.0132	0.0103	0.0092	0.0107	0.0041
1996	848	415	670	603	890	0.0101	0.0087	0.0111	0.0130	0.0083
1997	800	381	598	624	1186	0.0090	0.0074	0.0088	0.0139	0.0147
1998	632	409	566	586	1457	0.0056	0.0085	0.0079	0.0122	0.0221
1999	548	418	605	530	1605	0.0042	0.0089	0.0090	0.0100	0.0269
2000	430	395	549	418	1597	0.0026	0.0079	0.0074	0.0062	0.0266
2001	139	123	242	153	714	0.0003	0.0008	0.0014	0.0008	0.0053
Total/ H_P	8438	4440	6373	5295	9793	***0.0941***	***0.0883***	***0.0872***	***0.0916***	***0.1145***

Panel B. Time Herfindahl Index: MFTS										
	Portfolio Frequency over Time					*Herfindahl Index for Each Portfolio across Years*				
Year	***P1***	***P2***	***P3***	***P4***	***P5***	***P1***	***P2***	***P3***	***P4***	***P5***
1990	155	50	87	44	45	0.0027	0.0031	0.0033	0.0020	0.0003
1991	203	70	88	78	68	0.0047	0.0062	0.0034	0.0061	0.0007
1992	277	98	137	81	92	0.0087	0.0121	0.0082	0.0066	0.0012
1993	323	78	115	58	89	0.0119	0.0077	0.0058	0.0034	0.0011
1994	349	77	144	74	116	0.0139	0.0075	0.0091	0.0055	0.0019
1995	364	89	155	118	164	0.0151	0.0100	0.0106	0.0140	0.0039
1996	335	75	174	117	243	0.0128	0.0071	0.0133	0.0138	0.0085
1997	293	72	163	102	334	0.0098	0.0065	0.0117	0.0105	0.0161
1998	233	99	153	101	383	0.0062	0.0123	0.0103	0.0103	0.0211
1999	220	68	138	101	427	0.0055	0.0058	0.0084	0.0103	0.0263
2000	153	85	110	84	454	0.0027	0.0091	0.0053	0.0071	0.0297
2001	59	30	45	38	220	0.0004	0.0011	0.0009	0.0015	0.0070
Total/ H_P	2964	891	1509	996	2635	***0.0943***	***0.0885***	***0.0902***	***0.0911***	***0.1177***

Note: P1 denotes the most optimistic portfolio; P2 denotes another optimistic portfolio – i.e., less optimistic than P1 and more optimistic than P3; P3 denotes the least optimistic portfolio – i.e., less optimistic than both P1 and P2; P4 denotes a less pessimistic portfolio than P5; P5 denotes the most pessimistic portfolio.

Table 6. Continued.

Panel C. Industry Herfindahl Index: MFFE							
	Industry Frequency						
Industry*	***Aggregate***	***P1***	***P2***	***P3***	***P4***	***P5***	H_{IND}
1[a]	4017	622	461	726	667	1541	***0.245***
2[b]	2514	498	249	555	377	835	***0.231***
3[c]	3018	705	374	588	470	881	***0.217***
4[d]	4452	971	611	1046	673	1151	***0.211***
5[e]	2035	557	228	340	303	607	***0.227***
6[f]	1787	541	240	238	293	475	***0.225***
7[g]	1011	344	178	173	121	195	***0.228***
8[h]	5829	1635	775	1082	806	1531	***0.219***
9[i]	4399	1167	601	719	770	1142	***0.214***
10[j]	4105	1111	542	691	552	1209	***0.224***
11[k]	1429	361	220	283	305	260	***0.205***

Panel D. Industry Herfindahl Index: MFTS							
	Industry Frequency						
Industry*	***Aggregate***	***P1***	***P2***	***P3***	***P4***	***P5***	H_{IND}
1[a]	921	186	116	232	104	283	***0.227***
2[b]	581	189	40	151	41	160	***0.259***
3[c]	753	306	82	121	104	140	***0.256***
4[d]	1042	345	131	272	120	174	***0.235***
5[e]	529	214	45	59	66	145	***0.274***
6[f]	629	194	47	56	59	273	***0.306***
7[g]	276	110	30	47	17	72	***0.272***
8[h]	1511	564	139	225	155	428	***0.261***
9[i]	1304	365	104	121	160	554	***0.289***
10[j]	1087	407	103	141	94	342	***0.272***
11[k]	362	85	54	85	74	64	***0.206***

* The following superscripts indicate *I/B/E/S* industry sectors: [a] Finance; [b] Health Care; [c] Consumer Non-Durables; [d] Consumer Services; [e] Consumer Durables; [f] Energy; [g] Transportation; [h] Technology; [i] Basic Industries; [j] Capital Goods; [k] Public Utilities.

Table 6. Continued.

Panel E. Stock Exchange Herfindahl Index: MFFE							
	Industry Frequency						
Industry	***Aggregate***	***P1***	***P2***	***P3***	***P4***	***P5***	H_{EX}
NYSE	24215	5549	3049	4482	3984	7151	***0.217***
AMEX	678	329	91	106	70	82	***0.303***
NASDAQ	9712	2634	1342	1853	1286	2597	***0.218***

Panel F. Stock Exchange Herfindahl Index: MFTS							
	Industry Frequency						
Industry	***Aggregate***	***P1***	***P2***	***P3***	***P4***	***P5***	H_{EX}
NYSE	6287	1868	580	1032	810	1997	***0.241***
AMEX	228	155	21	28	8	16	***0.492***
NASDAQ	2482	942	290	450	178	622	***0.259***

Table 7. Multiple Regression Models

This table reports the relationships between analysts' earnings forecasts and investors' earnings expectations and between the predicted *CAR*s under the *NEH* and the *REH*, and the regression results from the following models:

$$CAR_t = \alpha_1 P_1 + \alpha_2 P_2 + \alpha_3 P_3 + \alpha_4 P_4 + \alpha_5 P_5 + \beta_1 diffSize_t + \beta_2 diffBtoM_t + u_t$$

$$CAR_t = a_1 P_1 + a_2 P_2 + a_3 P_3 + a_4 P_4 + a_5 P_5 + b_1 \frac{FE_t}{STD_t} + b_2 diffSize_t + b_3 diffBtoM_t + \upsilon_t$$

$$CAR_t = a'_1 + a'_2 P_2 + a'_3 P_3 + a'_4 P_4 + a'_5 P_5 + b'_1 \frac{FE_t}{STD} + b'_2 \frac{FE_t}{STD} P_2 + b'_3 \frac{FE_t}{STD} P_3$$
$$+ b'_4 \frac{FE_t}{STD_t} P_4 + b'_5 \frac{FE_t}{STD_t} P_5 + b'_6 diffSize_t + b'_7 diffBtoM_t + \omega_t$$

where

CAR_t	= the 3-day [–2: 0] abnormal stock returns for a quarterly earnings announcement
P_p	= a dummy variables that equal one if an observation belongs to portfolio *p* and zero otherwise, *p* = 1, …, 5;
FE_t	= analysts' earnings forecast errors at quarter *t*;
A_i	= the actual quarterly earnings at quarter *t*;
F_t	= the most recent analysts' consensus forecasts for A_i;
STD_t	= the standard deviation of analysts' consensus forecasts at quarter *t*;
MVE_t	= $P_t \times Shr_t$;
P_t	= the closing stock price at the third month of quarter *t*;
Shr_t	= the number of common shares used to calculate EPS at quarter *t*;
$diffSize_t$	= the difference between log(MVE_t) and the grand mean of log(MVE_t) where $\log(MVE_t)$ = the logarithm of MVE_t;
$BtoM_t$	= $\frac{BVE_t}{MVE_t}$ where BVE_t = common equity (total) at quarter *t*;
$diffBtoM_t$	= the difference between $BtoM_t$ and the grand mean of $BtoM_t$; and
$u_t, \upsilon_t, \omega_t$	= identically and independently distributed random error terms.

Note that P_t, Shr_t, and BVE_t are extracted from *COMPUSTAT*.

Table 7. Continued.

Panel A. **Regression of CAR on Portfolio Dummies, diffSize, and diffBtoM without Interaction Terms** $CAR_t = \alpha_1 P_1 + \alpha_2 P_2 + \alpha_3 P_3 + \alpha_4 P_4 + \alpha_5 P_5 + \beta_1 diffSize_t + \beta_2 diffBtoM_t + u_t$				
	Mean-Frequency Forecast Error (MFFE) Method		***Mean-Frequency Time-Series (MFTS) Method***	
Coefficient	***Estimate***	*Pr* > |*t*|	***Estimate***	***Pr* > |*t*|**
α_1	0.00264	<.0001	0.00231	0.0400
α_2	0.00349	<.0001	0.00212	0.2880
α_3	0.00417	<.0001	0.00450	0.0027
α_4	0.00362	<.0001	0.00226	0.1926
α_5	0.00296	<.0001	0.00340	0.0016
b_1	-0.00084	0.0001	-0.00133	0.0021
b_2	0.00515	<.0001	0.00515	0.0153
Pair-wise Comparison	***F-Value***	***Pr* > |*F*|**	***F-Value***	***Pr* > |*F*|**
$\alpha_1 = \alpha_2$	0.67	0.4145	0.01	0.9336
$\alpha_1 = \alpha_3$	2.59	0.1078	1.33	0.2491
$\alpha_1 = \alpha_4$	0.95	0.3309	0.00	0.9821
$\alpha_1 = \alpha_5$	0.14	0.7111	0.46	0.4967
$\alpha_2 = \alpha_3$	0.39	0.5323	0.90	0.3420
$\alpha_2 = \alpha_4$	0.01	0.9049	0.00	0.9572
$\alpha_2 = \alpha_5$	0.27	0.6057	0.32	0.5740
$\alpha_3 = \alpha_4$	0.28	0.5979	0.97	0.3256
$\alpha_3 = \alpha_5$	1.83	0.1765	0.36	0.5466
$\alpha_4 = \alpha_5$	0.49	0.4821	0.33	0.5676
F-value	23.43		6.78	
Pr > F	<.0001		<.0001	
R-square	0.0061		0.0068	
Adj R-sq	0.0059		0.0058	

Table 7. Continued.

Panel B.
Regression of CAR on Portfolio Dummies, FE, diffSize, and diffBtoM without Interaction Terms

$$CAR_t = a_1P_1 + a_2P_2 + a_3P_3 + a_4P_4 + a_5P_5 + b_1\frac{FE_t}{STD_t} + b_2diffSize_t + b_3diffBtoM_t + \upsilon_t$$

	Mean-Frequency Forecast Error (MFFE) Method		***Mean-Frequency Time-Series (MFTS) Method***	
Coefficient	***Estimate***	*Pr > |t|*	***Estimate***	***Pr > |t|***
a_1	**0.00359**	<.0001	**0.00427**	0.0001
a_2	0.00368	<.0001	0.00275	0.1628
a_3	0.00424	<.0001	0.00426	0.0040
a_4	0.00293	0.0001	0.00148	0.3868
a_5	**0.00178**	0.0018	**0.00214**	0.0453
b_1	0.00208	<.0001	0.00183	<.0001
b_2	-0.00088	<.0001	-0.00125	0.0035
b_3	0.00623	<.0001	0.00540	0.0100
Pair-wise Comparison	***F-Value***	***Pr > |F|***	***F-Value***	***Pr > |F|***
$a_1 = a_2$	0.01	0.9307	0.46	0.4992
$a_1 = a_3$	0.49	0.4860	0.00	0.9967
$a_1 = a_4$	0.43	0.5119	1.78	0.1818
$a_1 = a_5$	**4.28**	**0.0385**	1.76	0.1848
$a_2 = a_3$	0.28	0.5993	0.37	0.5413
$a_2 = a_4$	0.44	0.5069	0.23	0.6294
$a_2 = a_5$	3.53	0.0602	0.07	0.7862
$a_3 = a_4$	1.65	0.1984	1.53	0.2167
$a_3 = a_5$	7.75	0.0054	1.39	0.2380
$a_4 = a_5$	1.51	0.2187	0.11	0.7399
F-value	108.02		27.99	
Pr > F	<.0001		<.0001	
R-square	0.0277		0.0275	
Adj R-sq	0.0275		0.0265	

Table 7. Continued.

Panel C.
Regression of CAR on Portfolio Dummies, FE, diffSize, diffBtoM with Interaction Terms

$$CAR_t = a_1' + a_2'P_2 + a_3'P_3 + a_4'P_4 + a_5'P_5 + b_1'\frac{FE_t}{STD} + b_2'\frac{FE_t}{STD}P_2 + b_3'\frac{FE_t}{STD}P_3$$
$$+b_4'\frac{FE_t}{STD_t}P_4 + b_5'\frac{FE_t}{STD_t}P_5 + b_6'diffSize_t + b_7'diffBtoM_t + \omega_t$$

Panel C-1. Parameter Estimation

	Mean-Frequency Forecast Error (MFFE) Method		***Mean-Frequency Time-Series (MFTS) Method***	
Coefficient	***Estimate***	*Pr* > |*t*|	***Estimate***	***Pr* > |*t*|**
a_1'	0.00359	<.0001	0.00406	0.0004
a_2'	0.00012	0.9045	-0.00112	0.6209
a_3'	0.00066	0.4832	0.00005	0.9794
a_4'	-0.00056	0.5792	-0.00252	0.2286
a_5'	**-0.00160**	**0.0671**	**-0.00175**	**0.2799**
b_1'	0.00210	<.0001	0.00165	<.0001
b_2'	0.00031	0.2349	0.00075	0.1694
b_3'	0.00063	0.0235	0.00156	0.0062
b_4'	-0.00025	0.3378	0.00013	0.7826
b_5'	**-0.00031**	**0.1234**	**-0.00003**	**0.9186**
b_6'	-0.00089	<.0001	-0.00129	0.0025
b_7'	0.00629	<.0001	0.00538	0.0104
F-value	70.20		18.71	
Pr > F	<.0001		<.0001	
R-square	0.0283		0.0288	
Adj R-sq	0.0279		0.0273	

Table 7. Continued.

Panel C-2. Fixed and Marginal Effects				
	MFFE		***MFTS***	
Fixed Effects	***Estimate***	***Pr > |F|***	***Estimate***	***Pr > |F|***
a_1'	**0.00359**	<.0001	**0.00406**	0.0004
$a_1' + a_2'$	0.00371	<.0001	0.00294	0.1371
$a_1' + a_3'$	0.00425	<.0001	0.00411	0.0056
$a_1' + a_4'$	0.00303	<.0001	0.00154	0.3731
$a_1' + a_5'$	**0.00199**	0.0006	**0.00231**	0.0315
Marginal Effects	***Estimate***	***Pr > |F|***	***Estimate***	***Pr > |F|***
b_1'	**0.00210**	<.0001	**0.00165**	<.0001
$b_1' + b_2'$	0.00241	<.0001	0.00240	<.0001
$b_1' + b_3'$	0.00273	<.0001	0.00321	<.0001
$b_1' + b_4'$	0.00185	<.0001	0.00178	<.0001
$b_1' + b_5'$	**0.00179**	<.0001	**0.00167**	<.0001

VITA

Seung-Woog Kwag was born in the Republic of Korea on August 19, 1965. He was raised in Seoul, Korea and graduated from Hwanil High School in February 1984. He began his post-secondary education at Yonsei University, Seoul, Korea and received a Bachelor of Art in Psychology in February 1989. One year later he began graduate studies at Florida State University, Tallahassee, Florida where in May 1991 he received a Master of Science in Political Science. From 1992 to 1995 he served in the Korean Army as a first lieutenant. In 1996 he came back to the U.S. to continue his graduate studies. In August 1998 he received a Master of Science in Business administration from Texas Tech University, Lubbock, Texas. Immediately after receiving the masters' degree, he went to Finance Department in the College of Business Administration at the University of Tennessee, Knoxville in order to pursue doctoral studies. He received the Doctor of Philosophy degree in May 2002.

In March 2002 he accepted a faculty position as an assistant professor in the Department of Business Administration at Utah State University, Logan, Utah where he will pursue his new career.