Another Evidence of Chronic Bias in Earnings Forecasts: The Case of South Korea

Seung-Woog (Austin) Kwag*

*Utah State University

Abstract

This paper investigates the chronic bias in analysts' earnings forecasts for South Korean firms before and after the 1997 economic crisis. The empirical findings provide evidence that analyst forecast bias – optimism and pessimism – persists over time regardless of the two different economic periods: pre- and post-economic crisis.

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I. Introduction

The objective of this paper is to probe the chronic bias in historical earnings forecasts of analysts following South Korean firms that may draw reliable inferences about the direction and magnitude of contemporaneous forecasts.[1] The main questions are: (1) whether the chronic bias in historical earnings forecasts for South Korean firms has predictive power for current forecasts; (2) whether the 1997 economic crisis of South Korea has an impact on analysts' forecasting behavior by examining the chronic forecast bias of analysts before and after the economic crisis: pre-economic crisis period 1987~1996 and post-economic crisis period 1997~2002. Empirical findings are expected to enhance our understanding of analysts' forecasting behavior in emerging markets. Existing evidence for the United States (US) market suggests that chronic bias in analysts' earnings forecasts exists and abnormal-return investment opportunities may be caused by irrational market behavior (De Bondt and Thaler, 1987; Butler and Lang, 1991; Abarbanell, 1991; Stickel, 1991; Abarbanell and Bernard, 1992; La Porta, 1996; Easterwood and Nutt, 1999; Kwag and Shrieves, 2006).

Globalization has eliminated investment boundaries and investment companies have capitalized on knowledge about international market behavior. Specifically, emerging markets have increasingly provided the US investors with new investment opportunities.

[1] Among the existing studies of earnings forecasts, analyst optimism and pessimism are two distinct descriptors that characterize analysts' behavior in earnings forecasts. Following this convention, I use the term "bias" to denote either analyst optimism or pessimism hereafter. In addition, I use the term "chronic bias" to refer to the presence of a pattern of optimism or pessimism that pervades long series of forecasts.

As the first step to recognize new investment opportunities in emerging markets, the current paper investigates behavioral characteristics of leading investment decision makers – financial analysts – in South Korea and proposes that chronic bias in earnings forecast exists in the South Korean market and investors may capitalize on such bias. South Korea has undergone significant economic reforms since the International Monetary Fund (IMF) bailout program in 1997.[2] Many of the reforms, including improvement of corporate governance, the accounting system, and minority shareholder protection, have affected the South Korean capital market in important ways. For example, the elimination of all foreign exchange regulations and foreign investment ceilings has given foreign investors a greater role and brought more competition into the capital market.

Despite the progress, domestic and foreign confidence in the South Korean economy is not fully recovered. While this is due, in part, to the downturn of the global economy, blame also lies with significant differences between South Korea's Generally Accepted Accounting Practices (GAAP) and international standards represented by the US and United Kingdom (UK) GAAP. These differences have made South Korean financial statements less reliable to investors and potentially open to artificial management of earnings. For example, accounting and audit practices allowing off-balance-sheet transactions of material importance have undermined the credibility and soundness of the country as well as South Korean corporations. They should be improved so that any off-balance-sheet transactions of material importance will be reported and properly evaluated. Since the Financial Supervisory Commission (FSC) announced the adoption of new South Korean accounting standards closely modeled on those of the International Accounting Standards Committee (IASC) and US and UK GAAP, South Korean accounting standards have been getting closer to international standards. Although the new accounting standards appear to be different from the previous ones, the basic framework and content of the standards need to be further improved and fully enforced. Otherwise, the exceptions and differences from the US and UK standards will continue to concern investors.

Relatedly, South Korea is different from the US and UK in terms of investor protection and ownership structure. The US and UK have better legal protection of minority shareholders than South Korea. According to La Porta, Lopez-De-Silanes, and Shleifer (1998), the US and UK's aggregate shareholder rights index is significantly higher than South Korea's. La Porta et al. (1999) also provide evidence that the US and UK firms are more widely held compared with the South Korean firms. Using 20 percent as the criterion for control for a sample of 20 largest firms in the sample countries, they report that 100 percent of the firms in the UK and 90 percent of the firms in the US fit the widely held description, while only 55 percent of the firms in South Korea are considered widely held. Additionally, according to personnel with the Thomson Financial, the financial analysts following South Korean firms are different from the US analysts

[2] Reviewing the real causes of the 1997 economic crisis in Asia, quite a few researchers discuss the role of poor monetary policies in creating an inflationary boom. They suggest that poor monetary policies made by governments and/or the IMF lead to both currency and bank crises in the region (McLeod and Garnaut, 1998; Kim and Haque, 2002; Stiglitz, 2002).

specializing in the US firms in that they are either ones working for international investment companies or ones for South Korean investment companies.

An extensive body of the US literature reports that analysts are biased toward optimism (Butler and Lang, 1991; Abarbanell, 1991; Ackert and Athanassakos, 1997; Easterwood and Nutt, 1999; Givoly and Lakonishok, 1979; Hughes and Ricks, 1987; Cornell and Landsman, 1989; Teets, 1992; Alexander, Jr., 1992; Abarbanell and Bernard, 1992). Recently, Kwag and Shrieves (2006) find that analyst forecast bias (pessimism/optimism) is persistent. Debates on these topics are continuing in the US. All told, South Korea is a good candidate for a comparative study about the behavior of financial analysts. By studying the South Korean market given that chronic bias of analysts is a characteristic of the US market, this study will help answer whether chronic bias is a general or a market specific phenomenon. It will also examine the impact of the 1997 economic crisis on analyst forecast bias, since it will help better understand how a restructuring event affects the formation of analysts' earnings forecasts.

The paper advances as follows. Section 2 presents a brief review of the prior literature. Section 3 describes our data and the formation of portfolios and related measures. In section 4, I discuss the empirical findings. Section 5 concludes the paper.

II. Prior Studies

Previous empirical examinations of analyst bias in earnings forecasts provide evidence that optimism characterizes analysts' forecasting behavior. A few of the many studies supporting overall optimism in analysts' earnings forecasts include Abarbanell (1991), Francis and Phibrick (1993), La Porta (1996), and Easterwood and Nutt (1999). Abarbanell (1991) documents that analyst optimism characterizes the mean forecast error in each of the four years, 1981~1984. He also presents evidence that the frequency of analyst optimism surpasses that of analyst pessimism in every year during the 4-year period. Francis and Philbrick (1993) support the prediction that analysts report optimistic forecast to promote management relations. La Porta (1996) finds similar evidence that reported earnings tend to be lower than corresponding analysts' forecasts for almost all portfolios formed on the basis of growth forecasts. Easterwood and Nutt (1999) simultaneously investigate three hypotheses about analyst behavior – the rational hypothesis, the underreaction hypothesis, and the overreaction hypothesis – and find that analysts' reactions to new earnings information are contingent on the nature of information arrived. They show evidence 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.

In contrast to these findings, Brown (1996) presents evidence that 12 of the 18 quarters considered have higher percentage of positive forecast errors (i.e., reported earnings are greater than *I/B/E/S* analysts' forecasts) than that of negative forecast errors. Other evidence that raises doubt about the ubiquity of optimism is provided in Abarbanell (1999), Degeorge, Patel, and Zeckhauser (1999), and Abarbanell and Lehavy (2003). They find that even though analysts' earnings forecasts are, on average, optimistic, the frequency of pessimistic forecasts exceeds that of optimistic forecasts. This study casts doubt on the ubiquitous emphasis on analyst optimism as a predominant feature of earnings forecasts, and test the hypothesis that analysts show a spectrum of chronic forecasting behavior from optimism to pessimism that is useful in predicting current analysts' forecasts.

The finance literature contains only two studies that focus on the persistency in analyst optimism and pessimism (Butler and Lang, 1991; Kwag and Shrieves, 2006). Butler and Lang (1991) find that individual analysts are persistently optimistic or pessimistic relative to median consensus forecasts. Kwag and Shrieves (2006) recently develop metrics to form five behavior portfolios on the basis of the chronological record of two analyst forecast biases: optimism and pessimism. They use the formed portfolios to draw inferences about the direction and magnitude of analyst bias in contemporaneous forecasts. They provide evidence that analyst bias – both optimism and pessimism – persists long enough to be useful in drawing inferences about contemporaneous forecasts. While both persistent optimism and pessimism are observed in analysts' earnings forecasts, analyst optimism is, on average, the prevailing bias as documented in the previous studies. Along this line, this study tests the hypothesis that the proposed scheme in this paper has an ability to predict current forecasts – in other words implying that chronic bias in earnings forecast exists and forms successive bias.

III. Data and Formation of Behavior Portfolios

A. Formation of Behavior Portfolios

To classify South Korean firms into the portfolios based on analysts' past forecasting behavior; a portfolio is formed that combines the mean and frequency of forecast errors (*MFFE*). Annual analysts' forecasts and reported earnings are used to get necessary statistics - mean and percentage frequency of negative forecast errors.[3] The following equation estimates the mean forecast error for each firm.

$$MFE_i = \frac{1}{N}\sum_{t=1}^{N} FE_{it} \qquad (1)$$

where

MFE_i = the mean forecast error for firm i;

FE_{it} = the forecast error for firm i in year t ($= \frac{A_{it} - F_{it}}{|A_{i,t-1}|}$);

N = the number of forecast errors for firm i;

[3] Note that Kwag and Shrieves (2006) use the simple frequency of negative forecast errors instead of the percentage frequency of negative errors. I use the percentage frequency over the simple frequency, since I do not look back identical periods to compute the frequency as Kwag and Shrieves did (they looked back 20 quarters in each contemporaneous quarter). I/B/E/S data for South Korea is not as rich as those for the U.S.

A_{it} = the reported earnings per share (EPS) for firm *i* in year *t*;

F_{it} = the earliest median consensus earnings forecast for firm *i* in year *t*; and

$|A_{i,t-1}|$ = the absolute value of the reported EPS for firm *i* in year *t-1*.

The percentage frequency of negative forecast errors (*PFREQ*) for a firm is the percentile of the number of a firm's negative forecast errors over the total number of forecast errors, where the total number of forecast errors equals the sum of positive and negative forecast errors.[4]

Using means and percentage frequencies of analysts' forecast errors for the sample South Korean firms, quintile portfolios are formed; each of which represents a different degree of analysts' optimism or pessimism in earnings forecasts. The rationale for this portfolio formation is that observations in each portfolio should dominate observations in the next higher numbered portfolio on at least one of the two metrics, and be at least equivalent on the other. Observations with both *MFE* and *PFREQ* falling in either the first or second quintile, but which fall in the first quintile on at least one of the two measures, are in the optimistic portfolio, labeled P1. Observations with *MFE* and *PFREQ* falling in either the fourth or fifth quintile, but with one measure in fifth quintile, are in the pessimistic portfolio, labeled P5. As a result, there are five dominating portfolios representing the spectrum of analysts' forecasting behavior from the most optimistic (P1) to the most pessimistic group (P5). Table 1 summarizes the portfolio formation. The focus of this study is on the extreme portfolios (i.e., P1 and P5), since they are less likely associated with serious classification errors.

B. Sample

The data contain annual consensus earnings forecasts (the median forecasts) and reported *EPS* for 1990 to 2002 compiled from the I/B/E/S International Summary Tape. From 1990 through 2002, the initial sample includes 832 South Korean firms and 3640 firm-years. As described in the previous section, I use the earliest annual earnings forecast for the corresponding reported earnings is used and the forecast error computed. For a firm to be included in the sample at this stage, it should have at least five consecutive annual earnings records and matching forecasts. Then, observations lying above or below 4 times the standard deviation of the forecast errors are removed to mitigate the impact of extreme values.[5] The sample is divided into two sub-samples – holdout and historical samples. The holdout sample has the most recent observations (firm-years) of the firms and is used to assess the predictive power of the portfolio classification method employed in this research. The historical sample includes the rest of observations and is used to form the five dominating portfolios. The size of the historical sample is 1,699 firm-years (273 firms). The holdout sample consists of 273 firm-years from 273 firms. Note that both samples have the same number of firms, since the most recent observations are obtained from the existing 273 firms included in the historical sample.

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[4] That is, zero forecast errors, if any, are omitted to get the percentage frequency of negative forecast errors.

[5] Note that the major findings are not sensitive to the trimming method.

IV. Empirical Results

A. Descriptive Statistics

Panel A of Table 2 reports that for the historical sample, the mean forecast error is significantly negative with 60.80% of the observations having negative annual forecast errors (*NFE*). This confirms that analysts are, overall, chronically optimistic, consistent with prior studies (Butler and Lang, 1991; Abarbanell, 1991; Ackert and Athanassakos, 1997; Easterwood and Nutt, 1999). Similarly, the holdout sample shows consistent results. The mean forecast error (-0.8552) is significantly negative and the frequency of negative forecast errors (173) exceeds that of positive forecast errors (100). For the overall sample containing both the historical and holdout samples, the data (not shown) present that analysts are generally optimistic in both magnitude and frequency – i.e., negative mean forecast error and the frequency of positive forecast errors (*PFE*) < the frequency of negative forecast errors (*NFE*).

Panel B of Table 2 gives the statistics for the mean forecast error by portfolio, ranging from most optimistic (P1) to most pessimistic (P5). The formation of portfolios using the mean and frequency of forecast errors (*MFFE*) appears to identify, *ex post*, subsets of forecasts that run the gamut from optimistic (e.g., P1) to pessimistic (e.g., P5). This finding is not surprising per se, since by construction, portfolio means of forecast errors (*PMFE*) are monotone increasing in degree of chronic optimism or pessimism over the range of portfolios from P1 to P5. But the size of the variation in *PMFE* over the range of portfolios is striking. For example, *PMFE* ranges from -2.5583 in P1 to + 0.7964 in P5. Panel C of Table 2 also shows that the percentage frequency of negative forecast errors (=*NFE/N*) ranges from 80.98% (=345/426) in P1 to 35.31% (=137/388) in P5.

Despite the fact that differences are expected due to the manner of construction of the portfolios, these rather dramatic differences in *PMFE* and the percentage frequency of negative forecast errors from P1 to P5 are an indication of notable heterogeneity of analysts with respect to persistent optimism and pessimism. In particular, the finding on the differences in the distribution of negative forecast errors (*NFE*) for P1 and P5 implies that the heterogeneity is not traceable to occasional extreme values for forecast errors, especially provided that the most extreme observations have already been removed from the sample. These findings suggest that earnings studies should not focus on average analyst behavior and that forecast errors are drawn from different distributions.

According to Table 2, the portfolio formation using *MFFE* appears to have significant predictive power to identify current analyst optimism and pessimism. Panel B exhibits that the means of current forecast errors (*MCFEs*) closely follow *PMFEs* especially for *P1* and *P5*, and both are statistically significant. The percentage frequency of negative forecast errors for the holdout sample ranges from 84.7% (=61/72) in P1 to 35.3% (=24/68) in P5 and shows a consistent trend with that for the historical sample. For both P1 and P5, the binomial test rejects the null hypothesis that the percentage frequency of negative forecast errors is the same as that of positive forecast errors. This is true regardless of samples – historical and holdout. Specifically, analysts tend to issue negative forecast errors (i.e., optimistic forecasts) more frequently for P1, while they issue positive forecast errors (i.e., pessimistic forecasts) more frequently for P5.

B. A Non-Parametric Test of the Incremental Information in Bias Classification

The findings in the previous section suggest the presence of bias heterogeneity in forecasts including both optimism and pessimism. Next, a nonparametric test is employed to address whether ex ante classification of forecasts into optimistic and pessimistic groups can provide information about a subsequent forecast that is incremental to the information embodied in the prior year's forecast error. Panel A of Table 3 gives the two-way contingency for algebraic signs on the prior period (t-1) and contemporaneous (t) forecast errors for the overall historical and holdout samples. The number of observations and test statistics for the holdout sample are shown in parentheses. For the historical sample, the table shows that prior period "good news" has a 44.99% (=310/689) chance of being followed by another positive error, whereas prior period "bad news" has a 35.25% (=356/1010) chance of being followed by a positive error. Similar evidence is found for the holdout sample. These ratios are used to compute the theoretical frequency of Panels B and C by multiplying the marginal frequency of the contemporaneous forecast errors in the respective subsets for the optimistic and pessimistic cases by the ratio of the marginal frequency in the corresponding cell for the overall case.

Panel B provides a contingency table for the subset of 426 forecasts that are classified as optimistic (P1), along with a Chi-square test for whether the distribution in Panel B differs from that for the overall case. If the bias classification does not provide incremental information, given the prior period forecast error, then it would be expected that the relative frequency of positive and negative forecast errors to be the same in this subset as in the larger sample. That is, for the 89 forecasts where the lagged forecast error was positive, expectations are that about 40 (45% X 89) positive forecast errors would occur in period t along with 49 (=55% X 89) negative errors. For both positive and negative prior period forecast errors, there are significantly more negative contemporaneous forecast errors for P1 than would be expected if the portfolio classification were meaningless. It is expected to have 49 negative contemporaneous forecast errors in response to prior good news and 218 negative errors in response to prior bad news. We observe, however, 80 and 266 negative forecast errors; a number that is significantly greater than the expected frequencies of 49 and 218. The same result is observed in the holdout sample. Following prior good and bad news, 7 and 40 negative contemporaneous forecast errors are expected respectively. Different from this expectation, 13 and 49 contemporaneous errors turn out to be negative. The difference is significant at the 1% level.

Panel C of Table 3 provides a similar analysis for the subset of forecasts classified as most pessimistic (P5). In this case, regardless of the sample and whether the prior forecast error was positive or negative, the period *t* forecast is more likely to be positive relative to the frequencies exhibited in the overall sample. For the historical sample, the observed positive forecast errors are 156 and 95 that are significantly greater than the theoretical frequencies of 110 and 51. Similarly, 32 and 12 positive errors are observed for the holdout sample. These are significantly greater than the expected, 22 and 6. Like the results for the optimistic forecasts, the *ex ante* portfolio classification methodology does provide insight that is incremental to that embedded in the prior period's forecast error.

C. Impact of Economic Crisis on Analyst Bias: A Robustness Check

In this section, I examine the impact of the 1997 economic crisis of South Korea on analyst forecast bias. The pre-economic crisis periods include years from 1990 to 1996, while the post-economic crisis periods cover years from 1997 to 2002. Table 4 provides a summary of binomial and Chi-square test results. Overall, the binomial test suggests that historical forecast errors have predictive power to detect analyst optimism and pessimism in current earnings forecasts regardless of the economic periods.

Chi-square test results for the pre-economic crisis period are mostly consistent with those for the whole period including both pre- and post-economic crisis periods. Except for the holdout sample in the pre-economic crisis period, there are significantly more negative (positive) contemporaneous forecast errors for P1 (P5) irrespective of the type of prior news. This confirms the proposition that the bias classification does provide incremental information about contemporaneous analyst forecast and further suggests that chronic bias in earnings forecasts exists. Although it seems that the test statistics are somewhat stronger for the post-economic crisis period than the pre-economic, bias persistency is observed in both periods.

V. Conclusions

The descriptive statistics suggest that analysts following South Korean firms are, on average, chronically optimistic in terms of both magnitude and frequency of optimistic forecasts. This is consistent with results documented in the U.S. studies. The formed portfolios display dramatic differences in mean forecast error and percentage frequency of negative forecast errors and this is an indication of heterogeneous forecasting behavior of analysts following South Korean firms. These suggest that earnings studies for such firms should not focus on average analyst behavior.

The data also show that chronic bias of analysts has significant predictive power to identify current analyst optimism and pessimism. Descriptive statistics and binomial test results are very consistent across historical and holdout samples. The optimistic (pessimistic) historical portfolios reliably match with the optimistic (pessimistic) holdout portfolios both in bias magnitude and in frequency of negative forecast errors. These results are robust to the economic periods – pre- and post-economic crisis of South Korea. In addition, nonparametric tests conditioning serial correlation on ex ante bias classification suggest that the bias classification used in the paper includes significant incremental information about analysts' earnings forecasts, consistent with Kwag and Shrieves (2006). This phenomenon persists through the whole period including both pre- and post-economic crisis periods. Further international research on investor reaction to chronic bias in earnings forecasts is warranted.

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Table 1. Portfolio Formation

To form portfolios of interest, a joint method of the mean and frequency of analysts' forecast errors is used. The mean forecast error (*MFE*) is the average of forecast errors during the whole existing period of a firm in I/B/E/S. The percentage frequency of negative forecast errors (*PFREQ*) for a firm is the percentile of the number of a firm's negative forecast errors over the total number of forecast errors, where the total number of forecast errors equals the sum of positive and negative forecast errors. Both measures, *MFE* and *PFREQ*, rank firms into quintiles (Q1 to Q5) resulting in 25 subsets when a 2×2 contingency table is constructed. The 25 subsets are redefined into 5 portfolios (P1, …, P5), such that each portfolio dominates (in the sense of greater optimism) every higher numbered portfolio on one of the two metrics, and is at least as optimistic on the other.

	MFE Rank				
Percentage Frequency (PFREQ) Rank	***Q1***	***Q2***	***Q3***	***Q4***	***Q5***
Q1	**P1** (143, 24)	**P1** (154, 24)			
Q2	**P1** (129, 24)	**P2** (145, 23)	**P2** (168, 24)		
Q3		**P2** (92, 14)	**P3** (83, 14)	**P4** (127, 21)	
Q4			**P4** (105, 14)	**P4** (165, 23)	**P5** (88, 18)
Q5				**P5** (142, 21)	**P5** (158, 29)

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

Table 2. Descriptive Statistics

Panel A presents the grand mean and median of annual forecast errors (*FE*) and the numbers (percentages) of positive, negative, and zero forecast errors for historical and holdout samples. *PFE* is the frequency of positive forecast errors; *NFE* is the frequency of negative forecast errors; *ZFE* indicates the frequency of zero forecast errors. Panel B reports portfolio means of historical and current forecast errors and *PMFE* is the mean of historical forecast errors; *MCFE* is the mean of current (holdout) forecast errors. The five portfolios consist of subsets of forecasts that run the gamut from most optimistic (P1) to most pessimistic (P5).

For historical and holdout samples, panels C and D summarize a nonparametric binomial test of the null hypothesis that the probability (*p*) of getting *PFEs* is 0.5 for all *n* trials – i.e., Ho: *p=0.5*. Note that "*n*" is the total number of *PFEs* and *NFE*s excluding *ZFE*s. Following Conover (1980; pp. 96-99), The test statistic (*T*) and the corresponding critical regions at the 5% and 1% levels is calculated as follows:

T = the number of *PFEs*;

LO5% (lower limit at the 5% level) = $np - 1.96\sqrt{np(1-p)}$;

UP5% (upper limit at the 5% level) = $np + 1.96\sqrt{np(1-p)}$;

LO1% (lower limit at the 1% level) = $np - 2.58\sqrt{np(1-p)}$;

UP1% (upper limit at the 1% level) = $np + 2.58\sqrt{np(1-p)}$.

Panel A. Forecast Errors: Mean and Frequency for Historical and Holdout Samples

N	***Mean***	***PFE***	***NFE***	***ZFE***
1,699	-0.7141***	666 (39.20%)	1033 (60.80%)	0 (0.00%)
273	-0.8552***	100 (36.63%)	173 (63.37%)	0 (0.00%)

Panel B. Descriptive Statistics for *MFE and MCFE*, by Portfolio

	N	***PMFE***	***MCFE***[a]
P1	426 (72)	-2.5583***	-2.6947***
P2	405 (61)	-0.7839***	-0.8687***
P3	83 (14)	-0.4851***	-0.7142
P4	397 (58)	-0.1898***	-0.2998
P5	388 (68)	0.7964**	0.6018**
Total	1,699 (273)		

Panel C. Nonparametric Binomial Test for the Historical Sample

	N[b]	***PFE***	***NFE***	***T***	***LO1%***	***UP1%***	***LO5%***	***UP5%***
P1	426	81	345	81 ***	186	240	193	233
P2	405	121	284	121***	177	228	183	222
P3	83	30	53	30 **	30	53	33	50
P4	397	184	213	184	173	224	179	218
P5	388	251	137	251***	169	219	175	213
Total	1,699							

Table 2. Continued.

Panel D. Nonparametric Binomial Test for the Holdout Sample								
	N [b]	***PFE***	***NFE***	***T***	***LO1%***	***UP1%***	***LO5%***	***UP5%***
P1	72	11	61	11***	25	47	28	44
P2	61	13	48	13***	20	41	23	38
P3	14	6	8	6	2	12	3	11
P4	58	27	31	27	19	39	22	36
P5	68	44	24	44**	23	45	26	42
Total	273							

[a] Since *MCFE* represents the portfolio mean of current forecast errors (not historical), the number of observations for each portfolio is smaller than "*N*". The total number of observations is 401.

*** Significant at the 1% level
** Significant at the 5% level
* Significant at the 10% level

Table 3. Chi-Square Tests Conditioning Serial Correlation on *Ex Ante* Bias Classification

Panels show nonparametric Chi-square tests to test the null hypothesis that getting positive forecast error (*PFE*) at the contemporaneous year is equally likely as getting negative forecast error (*NFE*). Each subset contains the number of *FE* sign transitions (excluding no sign transitions) that firms make from year *t-1* to the contemporaneous year *t*. The test statistic (Chi-square; χ^2) and theoretical frequencies are calculated as follows:

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

where O_d = the observed frequency of *FE* sign transitions for subset *d*, *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). Refer to Gujarati (1988; pp. 373-375). The theoretical frequency is computed by multiplying the marginal frequency of the contemporaneous forecast errors in the respective subsets by the ratio of the marginal frequency in the corresponding cell for the overall case. For example, the theoretical frequency for observing a PFE_t , contingent on having experienced a PFE_{t-1} , is: 89 × (44.99%) = 40. The theoretical prediction in Panels B and C is formed on the basis of the marginal numbers in Panel A to facilitate a direct comparison of the incremental effect of chronic optimism or pessimism in the firm's forecasting history. Note that the numbers in parentheses are frequencies and statistics for the *holdout* sample.

Panel A. Non-Parametric Chi-square Test: Overall Case					
	Observed			***Theoretical***	
	PFE at t	***NFE at t***	***Row Total***	***PFE at t***	***NFE at t***
PFE at t-1	310 (46)	379 (60)	*689* *(106)*	44.99% (43.40%)	55.01% (56.60%)
NFE at t-1	356 (54)	654 (113)	*1010* *(167)*	35.25% (32.34%)	64.75% (67.66%)
Column Total	*666* *(100)*	*1033* *(173)*	*1699* *(273)*	*N/A*	*N/A*

Panel B. Non-Parametric Chi-square Test: Optimistic Case					
	Observed			***Theoretical***	
	PFE at t	***NFE at t***	***Row Total***	***PFE at t***	***NFE at t***
PFE at t-1	9 (0)	80 (13)	*89* *(13)*	40 (6)	49 (7)
NFE at t-1	71 (10)	266 (49)	*337* *(59)*	119 (19)	218 (40)
Column Total	*80* *(10)*	*346* *(62)*	*426* *(72)*	*159* *(25)*	*267* *(47)*
χ^2 **=73.437 (16.350)**; *df*=1	$\chi^2(1)$ =2.71(10%); 3.83 (5%); 6.63 (1%)				

Table 3. Continued.

Panel C. Non-Parametric Chi-square Test: Pessimistic Case					
	Observed			***Theoretical***	
	PFE at t	***NFE at t***	***Row Total***	***PFE at t***	***NFE at t***
PFE at t-1	156 (32)	88 (19)	*244* *(51)*	110 (22)	134 (29)
NFE at t-1	95 (12)	49 (5)	*144* *(17)*	51 (6)	93 (11)
Column Total	*251* *(44)*	*137* *(24)*	*388* *(68)*	*161* *(28)*	*227* *(40)*
χ^2 **= 94.932 (17.046)**; *df*=1 $\chi^2(1)$ =2.71(10%); 3.83 (5%); 6.63 (1%)					

Table 4. Binomial and Chi-square Tests: Pre- versus Post-Economic Crisis Periods.

This table presents descriptive statistics and test results reported in Tables 2~4 over two different economic periods: pre- and post-economic crisis periods. The five portfolios consist of subsets of forecasts that run the gamut from most optimistic (P1) to most pessimistic (P5).

	Pre-Economic Crisis Period: (1990-1996)		Post-Economic Crisis Period: (1996-2002)	
	Historical	Holdout	Historical	Holdout
Binomial Test	P1*** and P5**	P1*** and P5**	P1*** and P5***	P1*** and P5**
Chi-square: Optimistic Case	χ^2 = 24.859 (consistent)	χ^2 = 0.530 (not consistent)	χ^2 = 51.245 (consistent)	χ^2 = 7.526 (consistent)
Chi-square: Pessimistic Case	χ^2 = 29.533 (consistent)	χ^2 = 4.415 (consistent)	χ^2 = 80.531 (consistent)	χ^2 = 20.005 (consistent)
Chi-square Critical Values with *df*=1: χ^2 (1) = 2.71 (10%); 3.83 (5%); 6.63 (1%)				