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**IS ACCRUAL MISPRICING RELATED TO INVESTOR SOPHISTICATION?
EVIDENCE FROM ANALYSTS' FORECASTS**

by

Rafal Szwejkowski

**A Dissertation submitted to the Faculty of the
COMMITTEE ON BUSINESS ADMINISTRATION**

**In Partial Fulfillment of the Requirements
For the Degree of**

**DOCTOR OF PHILOSOPHY
WITH A MAJOR IN MANAGEMENT**

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THE UNIVERSITY OF ARIZONA

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and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy

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TABLE OF CONTENTS

ABSTRACT.....	7
CHAPTER 1 – INTRODUCTION.....	8
CHAPTER 2 – THE NATURE OF ACCRUAL ACCOUNTING.....	14
2.1 The Nature of Accruals.....	14
2.2 Literature Review.....	18
2.2.1 Properties of Accounting Accruals.....	18
2.2.2 Managerial Discretion and Components of Accruals.....	20
2.3 Summary.....	22
CHAPTER 3 – ACCRUAL MISPRICING ANOMALY.....	23
3.1 Literature Review.....	23
3.2 Accrual Mispricing Anomaly.....	26
3.3 Financial Analysts and Accrual Mispricing.....	29
3.4 Financial Analysts and Accrual Mispricing: Testable Implications.....	30
3.4.1 The Relationship Between Analyst Forecast and Accruals.....	31
3.4.2 Analysts’ Response to Abnormal vs. Normal Accruals.....	33
3.4.3 The Impact of Analyst Following on Forecast Efficiency with Respect to Accruals.....	34
3.4.4 The Relationship Between Analyst Quality and the Propensity to Misinterpret Accruals.....	36
3.5 Summary.....	37
CHAPTER 4 – EMPIRICAL MODELS, SAMPLE SELECTION, AND RESULTS.....	39
4.1 Empirical Method.....	39
4.2 Models, Empirical Proxies, and Variable Definitions.....	39
4.2.1 Dependent Variable Specification.....	39
4.2.2 Measures of Accruals.....	40
4.2.3 Individual Analyst Forecasting Ability.....	42
4.2.4 Control Variables.....	43
4.3 Sample Selection.....	44
4.3.1 Descriptive Statistics.....	46
4.4 Empirical Models.....	47
4.4.1 Hypothesis 1 and 2: Are Analysts Inefficient with Respect to Accruals?.....	47
4.4.2 Hypothesis 3: Analysts’ Response to Normal and Abnormal Components of Accruals.....	50

TABLE OF CONTENTS – *Continued*

4.4.3 Hypothesis 4: The Effect of Analyst Following on Efficiency of Consensus Forecasts with Respect to Accruals	52
4.4.4 Hypothesis 5: The Impact of Analyst’s Relative Forecasting Ability on their Propensity to Misprice Accruals.....	55
CHAPTER 5 – SUMMARY AND CONCLUSION	60
APPENDIX A - VARIABLE DEFINITIONS	63
APPENDIX B - TABLES.....	64
APPENDIX C - FIGURES	83
REFERENCES	89

ABSTRACT

The relationship between accrual inefficiency in analysts' forecasts and analyst following, analysts' forecasting ability, and the relative magnitude of discretionary accruals is analyzed. Results aid in answering two research questions: (1) whether the accrual mispricing anomaly has economic substance or is merely an artifact of missing risk factors; and (2) whether the observed financial analysts' response to accounting accruals is consistent with the accrual mispricing anomaly or its origins lie elsewhere.

Sloan [1996] provides evidence of abnormal market returns correlated with the prior year's accrual and cash flow components of earnings. Few possible explanations are presented in the literature for the observed phenomenon: the Naïve Investor Hypothesis suggests that market participants "fixate" on earnings figures and erroneously estimate earnings persistence without regard for the impact of accruals. Alternatively there are concerns that the observed abnormal returns are merely compensation for unaccounted risk factors and thus do not constitute a departure from market efficiency.

Results of this study provide evidence of accrual misinterpretation among financial analysts consistent with the pattern of mispricing that is observed in the market. This conclusion supports the view of accrual mispricing as a true market anomaly. Moreover, the naïve investor hypothesis is supported by the evidence that analysts' response to accounting accruals improves with their forecasting ability and that greater analyst following leads to consensus forecasts being more efficient.

CHAPTER 1 – INTRODUCTION

Accounting earnings are the most widely quoted measure of business performance and thus it is no surprise that information content of earnings is one of the primary areas of interest in accounting research. Such research has two objectives. First, it aims to determine how informative accounting earnings are in terms of explaining the current and the future performance of a firm. Second, it aims to shed light on the extent with which the market participants use information available in the earnings for setting their expectations of future earnings. My study advances the second objective by examining market participants' ability to use information in earnings, specifically the information in accruals and cash flows.

Cash flows and accruals have different consequences for future earnings. Cash flows are more likely to lead to sustained future profitability and therefore have relatively high predictive power with respect to future earnings; they are said to have *high persistence*. In contrast to cash flows, accounting accruals are less indicative of future earnings and are more likely to fluctuate from period to period. High levels of accruals are unlikely to repeat in the future; in other words, accruals are said to have *low persistence*.

If market participants were aware of the different implications of cash flows and accruals for future earnings, they would incorporate the higher persistence of cash flows, as compared to accruals, into their expectations of next year's earnings. If that were the case, when the annual earnings are announced we would not expect any earnings

surprises to be systematically correlated with the prior year's earnings and their components. If, however, market participants do not take account of the cash flow/accrual composition of past earnings and, despite the differences in persistence between the two, they expect both to have the same impact for the future earnings, then we should be able to observe earnings surprises related to this miscalculation. These earnings surprises would be negative for companies that report high accrual levels in the prior year's earnings and positive for companies with a high cash flow content in their past year's earnings. The negative surprise would be the natural outcome of investors' not taking account of the lower persistence of accruals and effectively overestimating future earnings, while the positive surprises would arise from exactly the opposite, the investors' underestimating of the persistence of earnings with a large, highly persistent cash flow component.

Earnings surprises consistent with the pattern described above have indeed been observed and manifest themselves as clusters of abnormal returns concentrated near the earnings announcement dates (Sloan [1996]). The existence of these abnormal returns is inconsistent with the notion that the market is efficient with respect to historical information. By definition, in an efficient market, investors are able to fully incorporate the information in accounting earnings released in the past. Regardless of whether the earnings consist mostly of cash flows or accruals, no trading strategy based on that information would consistently yield abnormal profits. Nevertheless, abnormal returns correlated with the prior year's accrual and cash flows suggest that abnormal profits could be realized through a trading strategy that consists of taking a long position in

lowest-accrual stocks and shorting the highest-accrual ones. Sloan [1996] demonstrates that such trading strategy appears to consistently generate positive abnormal returns year after year. According to him, this result is attributable to investors' overestimating of the persistence of the accrual component compared to the cash flow component of earnings. Consistent with this explanation, his analysis shows that the market behaves as if it does not differentiate between the two components of earnings, treating \$1 of cash flows exactly the same as \$1 of accruals, without regard for the lesser persistence of the latter.

Due to the difficulty in reconciling the efficient markets paradigm with the existence of abnormal returns, this pattern of earnings surprises associated with prior years' earnings is commonly referred to as the accrual mispricing *anomaly*. The extant literature to-date provides inconclusive and conflicting results regarding the nature of the accrual mispricing anomaly. The presumptive explanation for market anomalies claims that observed abnormal returns result from a mismeasurement due to omitted risk factors associated with high accrual firms. If that were the case, the observed accrual mispricing anomaly would simply be an artifact of research methodology.

The competing explanation for the accrual mispricing anomaly assumes that such abnormal returns genuinely exist and proposes that investors are not able to correctly incorporate the information in earnings components into their earnings expectations due to a lack of technical skill and knowledge. According to the naïve investor hypothesis, market participants ignore information regarding accruals and cash flows in their earnings expectations. Investor naiveté is a difficult proposition to defend, however, given general assumptions regarding investors' rationality.

Following Sloan [1996] the accounting literature on accrual mispricing--namely Ali, Hwang and Trombley [2000] and Bradshaw, Richardson, and Sloan [2001, forthcoming]--provides inconclusive and conflicting results. Consistent with the naïve investor hypothesis, Ali *et al.* expect sophisticated investors to be less susceptible to misunderstanding the time-series properties of earnings yet find no evidence that investor sophistication, measured by proxy of institutional ownership, has any impact on the magnitude of abnormal market returns associated with accrual mispricing. The lack of evidence supporting the naïve investor hypothesis leads them to side with the unaccounted risk factors hypothesis. Using analyst forecast data, Bradshaw, Richardson, and Sloan [forthcoming, 2001] point out that financial analysts also overestimate the persistence of accruals in their forecasts. Contrary to the conclusions of Ali, Hwang and Trombley [2000], the Bradshaw, Richardson and Sloan study proposes that, apart from specific incentives faced by analysts, inefficient forecasting techniques are responsible for biased forecasts. While this proposal is consistent with the naïve investor hypothesis, the authors provide no concrete evidence as support.

In this study I complement the research by Bradshaw, Richardson and Sloan to substantiate the claims that financial analysts may be inefficient with forecasting earnings due to their inability to account for differences in persistence between accruals and cash flows. In addition I provide more direct evidence regarding the naïve investor hypothesis using financial analysts' forecasts. To the extent that the conclusions reached regarding financial analysts can be generalized to all market participants, the evidence can either

corroborate the findings of Ali *et al.* and the omitted risk factor hypothesis, or can provide support for the conclusions of Bradshaw *et al.* and the naïve investor hypothesis.

The results presented in this study aim to provide further evidence for the viability of the naïve investor hypothesis as an alternative to the omitted risk factors hypothesis. To accomplish this goal I examine the cross-sectional patterns of financial analysts' responses to the accrual component of earnings. Unlike studying anonymous market trading activity, using financial analysts as the subject of this study presents an opportunity to single out each analyst and use their track record to address the question at the root of the naïve investor hypothesis: Do all market participants exhibit similar tendencies to overestimate the persistence of accruals; or, as their sophistication increases, are they able to incorporate knowledge of the lower persistence of accruals into their earnings expectations? I predict, consistent with the claims of the naïve investor hypothesis, that individual analysts respond differently to prior period accruals. I test for this in two ways: one is by examining the impact of analyst following on the accrual efficiency of consensus forecasts, and another by establishing an inverse relationship between the quality of analysts and their propensity to misinterpret accruals. I further separate accounting accruals into normal and abnormal components and examine whether the abnormal accrual component is the main factor affecting analysts' forecasts, an expectation consistent with Xie's [forthcoming] findings concerning abnormal accrual mispricing.

There are two contributions stemming from the research presented in this paper. First, by investigating the correlation between the efficiency of earnings forecasts with

respect to prior period accruals and analysts' individual forecasting abilities, I provide affirmative evidence for the naïve investor hypothesis. According to this hypothesis, the ability to incorporate the value-relevance of historical accounting information varies among market participants. Using analyst forecast data, it is possible to compare measures of each analyst's forecasting ability and thus test that prediction. Second, I establish a link between analysts' track records and accrual mispricing and explicitly focus on abnormal accruals as potential causes of analysts' inefficiency.

Based on cross-sectional analysis of analysts' forecast from I/B/E/S databases, my results demonstrate that while financial analysts are not entirely efficient with respect to accruals, their ability to account for accruals increases with their level of sophistication, or forecasting ability. For average- and above-average quality analysts the accrual inefficiency is smaller than for low-quality analysts, and is particularly attributable to abnormal accruals. By contrast low-quality analysts as a group are prone to misinterpret both normal and abnormal accruals alike. These results, indicating that analysts' quality improves their likelihood of efficiently using the information in accruals, are consistent with the predictions of the naïve investor hypothesis and support its viability as the underlying cause of accrual mispricing.

CHAPTER 2 – THE NATURE OF ACCRUAL ACCOUNTING AND MARKET VALUATION OF ACCRUALS

2.1 The Nature of Accruals

Financial reporting is one of the fundamental objectives of accounting. The goal of financial reporting is to provide information that is useful in making business and economic decisions. As an outcome of a complex process of gathering and classifying business information, financial reports provide standardized information to shareholders, creditors, the general public, and the government. Information from financial statements is widely used for valuation and evaluation purposes, often to arrive at fundamental estimates of enterprise value. While financial statements contain myriad value-relevant disclosures about the firm and its characteristics, accounting earnings are the most prominent and fundamental result of financial accounting. Indeed, the Financial Accounting Standards Board in its *Statement of Financial Accounting Concepts No.1* [1978] stated:

The primary focus of financial reporting is information about earnings and its components.

Unambiguously, the FASB recognized the importance of a standardized summary measure of company performance. Even more importantly, within the same statement, the FASB stressed the informational objective of financial reporting. The informational

objective states that financial statements should provide their users with information regarding future cash flows and their timing:

Financial reporting should provide information to help investors, creditors, and others assess the amounts, timing, and uncertainty of prospective net cash inflows to the related enterprise. (FASB [1978])

The main weakness of current cash flow as a measure of current performance, and as an indicator of future performance, is its disregard for the inevitable timing differences between completion of work or service and the receipt of payment. Rarely ever does the timing of cash inflows and outflows associated with a particular economic activity overlap perfectly. Even in a relatively primitive business system the outflows usually precede the expected inflow or vice versa. As business systems grow and become more sophisticated, the adequacy of current cash flows as indicators of future cash flows deteriorates further. In order to overcome this limitation of cash flows, accounting must use a measure that is consistent with the principle of *matching* and the principle of *recognition*. The matching principle requires that revenues and expenses are recognized in a manner that takes account of the time difference between incurred expenses and expected revenues. In accordance with the recognition principle, revenues should be recognized when they are earned and expenses should be recognized when incurred. Cash flow accounting clearly fails to meet these objectives. In order to achieve the goal of properly aligning business expenses incurred and the receipt of revenues corresponding to those expenses, accounting earnings must contain the cash flow

information combined with a non-cash component. We refer to this component as *accruals*.

The use of accruals gives accounting earnings an advantage in accurately capturing the present condition and future economic performance of a firm. Consequently, accrual accounting is the cornerstone of modern financial reporting, and that fact is explicitly recognized by the FASB in its *SFAC No. 1* [1978]:

Information about enterprise earnings based on accrual accounting generally provides a better indication of an enterprise's present and continuing ability to generate favorable cash flows than information limited to the financial effects of cash receipts and payments.

The use of accrual accounting does not come without tradeoffs. The main thrust of criticism against accrual accounting is that it sacrifices reliability and verifiability in order to achieve its superior level of informativeness. The sacrifice of reliability stems from the stipulation that, in contrast to reported cash flows, accounting accruals are subject to managerial estimation and judgment. As a result they leave room for discretion and misinformation. Management might use discretion in reporting accruals in a prudent manner, to enhance the information contained in earnings and signal their private information about the future business prospects, but depending on circumstances and incentives it might also choose to opportunistically manipulate earnings. Auditors verify management's estimates and judgments in financial reports, but they have limited ability to scrutinize accruals due to the majority of accruals' dependence on subjective managerial judgment of future events (e.g., bad debt and loan loss reserves, warranties,

pension costs, leases, contingent liabilities, and adjustments of inventories and fixed assets from asset impairment).

Despite considerable vulnerability to manipulation, accounting earnings have proven to be a superior measure of firm performance and future profitability. Accounting literature has repeatedly confirmed that accounting earnings are a superior predictor of future cash flows and firm value (Penmann and Sougiannis [1998], Dechow, Kothari, and Watts [1998]). Moreover, evidence suggests that market participants incorporate additional information contained in earnings over and above cash flow figures (Barth, Beaver, Hand, and Landsmann [1999]). The research also shows that information about earnings components is incrementally useful compared to the information in the aggregate earnings measure (Barth, Cram and Nelson [2001]).

The next two sections review the literature on the empirical assessment of the relative usefulness of accounting earnings as indicators of the current and future performance of an enterprise. I place emphasis on the incremental information content of accounting earnings over cash flows and on the impact of managerial discretion on the usefulness and quality of reported earnings.

2.2 Literature Review

2.2.1 Properties of Accounting Accruals

Investment professionals and business-related press often challenge the usefulness of accounting earnings in firm valuation. Cash flows and their timing are the cornerstone of traditional equity valuation (the discounted cash flow model). Many professionals voice the opinion that to improve consistency it is cash flows, not earnings, that should be used to forecast future cash flows. According to such critics, earnings suffer from noise and manipulation and thus are not valuable from the perspective of security pricing. This is often accompanied by anecdotal evidence of abuse of accounting discretion by opportunistic management.

Accounting literature has examined the ability of accounting earnings to capture value relevant information incremental to pure cash flows. Dechow [1994] assumes that if accrual earnings are indeed a superior summary measure compared to cash flows, the association between accrual earnings and security returns should be stronger than the correlation between cash flows and returns. Dechow also hypothesizes that since accrual accounting is designed to overcome the matching problem of revenues and expenses, the superiority of accrual earnings over cash flows as a summary measure should be particularly apparent for firms that are likely to suffer from long operating cycles, those in environments forcing volatile changes in working capital, and firms engaged in financing activities. Using market returns over varying horizons as the dependent variable and comparing the explanatory power (R^2) of cash flows versus accrual earnings

in separate models, she finds that accrual earnings are better indicators of firms' performance (as measured by market returns) and that the relative superiority of accounting earnings increases as (1) the time horizon decreases, as (2) the relative magnitude of the accrual component in earnings increases, as (3) the length of the operating cycle increases, and as (4) the volatility of financing activities increases. Dechow also finds that the improvement in explanatory power of earnings comes mainly from short-term working capital accruals and not from long-term accruals such as depreciation charges.

Penman and Sougiannis [1998] arrive at conclusions similar to those in Dechow [1994] although their focus and methodology are different. The paper by Penman and Sougiannis compares the predictive ability of several forms of the residual income model. They find that the specifications of the residual income model that use accounting earnings are superior to alternative specifications that use cash flows or dividends. The authors conclude that

[...] equity valuations based on forecasting GAAP accrual earnings and book values have practical advantages over forecasting dividends and cash flows. Accrual accounting has the feature of bringing the future forward in time in accruals and, by the accounting for operating assets, excluding investment expenditures as a charge against cash flow payoffs from operations. In addition it (in principle) matches the cost of investments against inflows from investments in time through depreciation allocations. This facilitates valuing firms from forecasts of payoffs over relatively short horizons.

While Dechow [1994] demonstrates that, in effect, accounting earnings, including accruals, have superior association with contemporaneous returns, Penman and

Souginannis [1998] show that accounting earnings are also superior in forecasting future stock prices using the residual income valuation model.

Barth, Beaver, Hand and Landsman [1999] further explore the components of earnings: cash flows and accruals. Using the residual income valuation model, they show that, both the valuation multiples on cash flows, and accruals increase with the size of accruals.

Dechow, Kothari and Watts [1998] use an analytical model of the accounting earnings process to demonstrate that accounting earnings are the best predictor of future cash flows and demonstrate lower variance in prediction errors using accounting earnings compared to cash flows. In an extension of the model in Dechow, Kothari and Watts [1998], Barth, Cram, and Nelson [2001] examine the ability of accounting earnings to predict future cash flows and conclude that the predictive power of accounting earnings with respect to future cash flows can be enhanced by disaggregating earnings into cash flow and accrual components. Given earlier results in the literature demonstrating differential persistence of each component (e.g. Sloan [1996]), the later results found in Dechow *et al.* and Barth *et al.* are not surprising.

While accounting research supports the basic intuition behind the conceptual framework of accrual accounting, the criticism remains that earnings may become misleading due to the opportunistic use of managerial discretion. The role of discretionary accruals is reviewed in the next section.

2.2.2 Managerial Discretion and Components of Accruals

The forward-looking character of accruals, so advantageous from the standpoint of the matching and recognition principles, comes at a cost. Accruals are one of the elements of the accounting framework where management can influence the numbers by changing assumptions and estimates. This ability of management to influence reported earnings has important implications for the quality and reliability of financial accounting. Study of managerial discretion in financial reporting is one of the central issues in financial accounting theory and is one of the major issues in the regulatory process.

Professional literature and the regulators usually portray managerial discretion in negative light. The SEC has increasingly focused on potential abuses of discretion as reflected in a recent speech dated April 26, 2001, by SEC commissioner Isaac C. Hunt:

Current market conditions may increase the pressure on companies to meet past or projected earnings levels. As a result, management may be tempted to engage in "not so" generally accepted accounting principles [...] decreasing "quality of earnings" reported by companies. [...] Using this type of smoke-and-mirrors to mislead investors ultimately will harm a company, as well as investors' confidence in our financial reporting system as a whole.

In fact, SEC officials have mentioned the issue of earnings management in the majority of their 2001 communications to financial industry professionals. Given its oversight role, it is understandable that the SEC is concerned about an issue that it perceives may potentially lead to fraud and misallocation of capital. The accounting literature approaches this subject in a comprehensive manner, recognizing three dimensions where discretionary behavior occurs: (1) within the agency theory framework, involving usually compensation contracting agreements between management and the owners of a

company where discretion over reported earnings plays a part in achieving an optimal risk-sharing solution; (2) in the information asymmetry/moral hazard setting, where management is better informed than investors and uses accruals to signal true persistence of earnings and to reduce earnings variability (“income smoothing”), improving earnings predictability; and (3) in third-party contracting, most commonly involving tax minimization and regulatory and political costs considerations. In all these roles managerial accounting discretion is potentially valuable from the shareholder perspective.

2.3 Summary

The prominence of accrual accounting, as the fundamental principle behind financial reporting, is generally supported by its regulators and practitioners while its merits are confirmed in the literature. Despite its shortcomings and vulnerability to manipulation, accrual accounting improves the information content of earnings and makes them more valuable from the investor’s standpoint. It is important, however, that the market correctly assesses the value-relevance of accruals in accounting earnings. In the next chapter, issues related to valuation of accounting accruals are described, and the accruals pricing anomaly is explained.

CHAPTER 3 – ACCRUAL MISPRICING ANOMALY

3.1 Literature Review

Accounting literature has found the accrual component of earnings to be of a lower persistence compared to the cash flow component. In other words, each dollar of cash flow in the current accounting earning of a company is more likely to constitute a permanent increase in earnings whereas a dollar of accrual earning has been shown to be more transitory (Dechow, Sabino and Sloan [1999]) and is less likely to persist in future periods' earnings.

Given this property of lesser persistence of accruals, financial markets should assign a lower valuation multiple to the accrual component of earnings. Evidence in the literature on this issue is mixed. On the one hand the market appears to value accruals accordingly based on their lower persistence, on the other hand the patterns of market returns associated with accruals suggest that accruals are not priced appropriately. Barth, Beaver, Hand, and Landsman [1999] examine relative valuation multiples on cash flows and accrual components using the residual income valuation model. It is apparent from their results that the market values the accrual component of earnings less than the cash flow component, which is consistent with the differential persistence of these components of earnings. Further evidence on the valuation of cash flows and accruals is given in Ali [1994] who examines the information content of the components of earnings, including working capital, in an earnings response coefficient framework. He shows that as the absolute value of earnings components increases, they become more transitory. His

results further indicate that both cash flows and working capital from operations are informative and are priced by the market, but the widest difference in valuation multiples occurs only for troubled companies.

One of the crucial characteristics of accounting accruals is that they are subject to managerial discretion and possibly to manipulation. In theory, accounting accruals can be divided into their discretionary and nondiscretionary components, each with different valuation impact. It is assumed that the discretionary component of accruals has lesser persistence than the nondiscretionary component and should be valued comparatively less. The value-relevance of the discretionary component of accruals was a subject of a number of studies but until Subramanyam [1996], most accounting research in this area concentrated on loan loss provisions (*e.g.*, Beaver *et al.* [1989], Wahlen [1994], Beaver and Engel [1996]). The results of these papers indicate that the market is able to isolate the discretionary component of loan loss provisions and attach a distinct valuation coefficient, lower than the one associated with the nondiscretionary component. General evidence that market participants price the discretionary component of accruals was not available until the publication of Subramanyam [1996], a market-wide, cross-sectional study. Subramanyam reasons that the observed market valuation for discretionary accruals is due to managerial discretion, which helps overcome informational asymmetry and smoothes income to reflect its true persistence, thus improving its predictability and comparability across time periods. While Subramanyam's results are valid, we must interpret them cautiously. The Jones model employed in his study is more likely to capture abnormal accruals, such that only some of them are discretionary. The ability of

this model to measure the discretionary and nondiscretionary components of accruals in a consistent and unbiased manner is questionable given the results of several recent studies (Dechow, Kothari and Watts [1998]; Dechow, Sabino and Sloan [1995]). In fact, the Jones model is mostly measuring what can be described accurately as *abnormal* accruals. While abnormal accruals were traditionally used in the literature as a proxy for discretionary accruals, researchers now shy away from reaching conclusions with respect to managerial discretion using the abnormal accruals models. Abnormal accruals models need modifications, such as firm-matching proposed in Guay, Kothari, and Watts [2000], or additional control variables found in Chan, Jegadeesh, and Sougiannis [2000] to provide an opportunity for test proper testing of earnings manipulation. Alternatively, methodologies such as the distributional analysis employed in Burgstahler and Dichev [2000] are able to offer evidence of earnings management without relying on an explicit modeling of the discretionary and nondiscretionary components of accruals.

In this study I use the Jones model to measure normal and abnormal accruals in order to emphasize that the difference in persistence of earnings components seems to be the driving force behind accrual inefficiency among financial analysts. In other words, I expect that as the persistence of earnings components decreases relative to cash flows, the extent of mispricing associated with them will increase. Thus, consistent with the results obtained by Xie [2001, forthcoming], the abnormal accruals with the least persistent and most transitory nature should result in a greater extent of mispricing compared to more persistent, normal accruals. Such analysis in essence uses normal and abnormal accrual

partitioning to highlight the differential persistence of earnings components as the central cause for the accrual mispricing phenomenon described in more detail in the next section.

3.2 Accrual Mispricing Anomaly

Given the results of studies cited in the previous section, it is apparent that the market takes into account the components of earnings such as cash flows and both normal and abnormal accruals. Nevertheless as shown in Sloan [1996], market participants may not be efficient in taking account of the differential persistence, and thus the value implications, of those components. The accrual mispricing anomaly described in Sloan [1996] provides initial motivation and the empirical setting for this study. Sloan's paper documents what seems to be a glaring market inefficiency with respect to historical accounting information. His results suggest that market participants behave as if they do not appreciate the difference between the implications of accrual and cash flow components for future earnings, essentially ignoring value-relevant information. Sloan shows that while market assessment of the overall persistence of earnings is correct, the market fails to take into account the differential persistence of accrual and cash flow components. Essentially, when a company reports a higher proportion of accruals in its overall earnings, the market expectation, on average, is not adjusted for the lower persistence of the accrual component. This oversight leads to a negative earnings surprise in the subsequent period. The opposite also holds true, such that low accrual earnings in the previous year are likely to result in a positive earnings surprise in the next year. Collins and Hribar [2000] demonstrate that accrual mispricing is separate from

other earnings-based anomalies such as post-earnings announcement drift. Further research by Xie [2001, forthcoming] shows that discretionary (or abnormal) accruals are mostly responsible for the observed anomalous returns. The results of Defond and Park [2000] seem to indicate that the abnormal returns are primarily associated with management use of discretion that goes contrary to earnings surprise. In other words when the earnings surprise is negative (positive) and managers use discretionary accruals to decrease (increase) the magnitude of the observed earnings, abnormal returns are larger, suggesting that the investors cannot instantly unravel earnings manipulation instantly. Instead, they adjust their expectations regarding future earnings of the company over time, leading to a series of abnormal returns, which in turn reflects the slow adjustment process.

Confronted with the existing evidence on market efficiency and potential violations of the efficient market paradigm, and assuming that the anomaly is not simply a research artifact, a question arises concerning the origin of the accrual mispricing anomaly. This question is puzzling since historical information is readily available to all market participants, and those lacking the wherewithal or sophistication to independently analyze the accounting information should observe certain signals, such as financial analysts' forecasts, in order to adjust their own earnings expectations.¹ The naïve investor hypothesis suggests that uninformed market participants are unable to recognize the time-series properties of earnings due to inadequate research and know-how, and the presence of transaction costs precludes market participants from exploiting profitable

trading strategies (see Bushan [1994]). Ali, Hwang, and Trombley [2000] test the naïve investor hypothesis as a potential explanation for the accrual mispricing anomaly. Their testing methodology is based on an expectation that, for stocks with greater participation from more sophisticated investors, the earnings announcement returns are likely to be lower when compared to the returns for stocks with lower participation from less sophisticated investors. They find no significant relationship between the level of abnormal returns associated with accrual mispricing and different measures of investor sophistication such as institutional investor following, company size, and the size of analyst following. The lack of association between these measures and abnormal returns surrounding earnings announcements is contrary to the expectations based on the naïve investor hypothesis. Ali *et al.* likewise contend that market mispricing anomaly is a spurious correlation prompted by inadequate control for unknown risk factors.

This paper is motivated by a possibility that the literature has failed to support the naïve investor hypothesis due to inadequate measures of investor sophistication. It is conceivable that not all institutional investors can overcome “earnings fixation” when that institutional investor following is not an adequate measure of investor sophistication. It is also possible that measuring analyst following does not capture the extent of sophistication of investors, that analysts’ forecasts are inefficient, or that investors do not subsume analysts’ forecasts into their earnings expectations. In order to address the questions and concerns associated with using proxies for investor sophistication, I turn to

Walther [1997] presents evidence that less sophisticated investors are likely to not utilize fully the information contained in analysts’ forecasts.

empirically analyzing the predictions of the naïve investor hypothesis using financial analysts, whose sophistication can be measured with better precision.

3.3 Financial Analysts and Accrual Mispricing

Financial analysts are a unique subset of market participants whose earnings expectations are publicly known. Studying each analyst's individual forecast history can yield significant results regarding the origins of the accrual mispricing anomaly. By our intuition financial analysts should prevent market anomalies based on historical accounting information and any other "market fixation" phenomena as well-informed professionals with expansive field expertise and privileged access to management. However, the literature shows that analysts' forecasts are biased and far from efficient (e.g. Ali, Klein, and Rosenfeld [1992], Mendenhall [1991]). Thus it can be expected that their forecasts should be susceptible to the same inefficiencies as those observed on the trading floor. Further study of financial analysts' forecasts would provide a valuable opportunity to gather additional evidence regarding the nature of the accrual mispricing anomaly. If the observed patterns of analyst inefficiency seem to conform to those detected in stock returns, this could lend additional support to the proposition that observed abnormal returns are not merely a research methodology artifact or an effect of unknown risk factors. Initial support for this expectations is available in Bradshaw, Richardson and Sloan [2001, forthcoming] and in Teoh and Wong [1998]. Bradshaw *et al.* test the correlation between the size of accruals in the prior year and analysts' errors in

predicting next year's earnings. If analysts efficiently process historical accrual information, there would be no significant statistical relationship between the level of accruals in the previous year and the forecast error. Evidence of such relationship implies that analysts do not correctly assess the level of accrual persistence in the companies they follow. Bradshaw *et al.* do find a significant negative correlation between the forecast errors and prior period accruals, a relationship decreasing in magnitude as the forecast horizon (from the time the forecast is released to the time earnings are announced) decreases, suggesting that this inefficiency decreases with time as less weight is given to last year's numbers. When analysts have difficulty fully incorporating the historical accounting information into their forecasts, this decreased reliance on prior year's earnings results in more efficient forecasts.

Results in Bradshaw *et al.* are similar to those obtained by Teoh and Wong [1998], who examine whether analysts are too credulous about the accounting numbers released by firms preparing for their IPO. Such firms face a substantial incentive to improve the attractiveness of their accounting numbers. Teoh and Wong find that the subsequent forecast errors are highly correlated with the magnitude of accruals in the immediate pre-IPO period, indicating that the financial analysts were indeed misled by management's discretion.

3.4 Financial Analysts and Accrual Mispricing: Testable Implications

Research relying on financial analysts' forecasts may provide additional evidence regarding the origins of accrual mispricing and the viability of the naïve investor

hypothesis. Empirical testing in this study is aimed at establishing the analyst inefficiency with respect to accruals (Hypotheses 1, 2, and 3) and discerning between possible patterns of this inefficiency, each with different implications regarding the source of accrual mispricing (Hypotheses 4 and 5). Specifically, Hypothesis 1 tests for the existence of the analyst inefficiency, Hypothesis 2 examines whether the type of accruals (working capital accruals versus total accruals, short- versus long- term) has differential impact on financial analysts' efficiency and, similarly, Hypothesis 3 examines the different impacts of normal and abnormal accruals on analysts' efficiency. The remainder of the study (Hypotheses 4 and 5) looks for the evidence of one of the two possible patterns of analysts' inefficiency, each with different implications for our understanding of the cause of accrual mispricing: either (1) analysts' responses are "fixed" and constant cross-sectionally, offering no support for the naïve investor hypothesis;² or (2) analysts' responses vary cross-sectionally and depend on each analyst's ability (or other individual analyst characteristics), providing support for the conclusion that accruals are mispriced due to deficiencies in the forecasting process. The following section describes each hypothesis and discusses their implications in detail.

3.4.1 The Relationship Between Analysts Forecasts and Prior Period Accruals

² An extremely unlikely scenario where a constant, or "fixed," inefficient response is due to across-the-board analyst naiveté is not considered plausible.

In partial accordance with Bradshaw *et al.* [2001, forthcoming], I examine the relationship between forecast errors and prior period accruals. Tests of Hypothesis 1 use the empirical model from Bradshaw *et al.*, which are extended by additional cross-sectional control variables for time (annual controls) and industry group. If financial analysts correctly estimate the persistence of the accrual component of earnings, their forecast errors would show no association with the prior period accruals. If, however, analysts systematically overestimate the persistence of the accruals, regressing forecast errors on prior period accruals should yield a negative coefficient on accruals. The hypothesis asserts the inefficiency of analysts with respect to prior period accruals:

Hypothesis 1: Current period earnings forecast errors are negatively associated with prior period accruals consistent with financial analysts overestimating the persistence of accruals.

If accrual bias in analysts' forecasts is attributable to inherent overoptimism in their assessment of accrual persistence, it is expected that total accruals (which include predictable and recurring components) would induce comparatively less bias than working capital accruals. This expectation, which is initially formulated in Bradshaw *et al.* but remains untested by the authors, is the basis for Hypothesis 2:

Hypothesis 2: Analysts are more likely to overestimate the persistence of working capital (or short-term) accruals compared to total (both short- and long-term) accruals.

Testing Hypothesis 2 is intended to reveal differences in analysts' response to different types of accruals. A test of Hypothesis 3 would likewise expose any impact of

differential persistence of normal and abnormal components of accruals. It is expected that the correlation between abnormal accruals are far more likely to induce overoptimistic bias in analysts' forecasts than normal accruals.

3.4.2 Analysts' Response to Abnormal vs. Normal Accruals

In addition to examining the difference in analysts' performance with respect to working capital and total accruals, I test for the independent possibility of a differential response to normal and abnormal components of accruals. As noted above, Xie [2001, forthcoming] shows the abnormal accruals to be correlated with abnormal returns. If financial markets have difficulty in setting correct earnings expectations for firms with high levels of abnormal accruals, we should observe a similar phenomenon in the forecasts of financial analysts. There are two possible reasons for financial analysts' difficulty with forecasting abnormal accruals. First, the abnormal accruals may be correlated with growth or volatility in a company's line of business. Predicting future earnings of companies with a high level of abnormal accruals may be more difficult than predicting earnings of companies in a steady state. In such case, given the well-known overoptimism in financial analysts forecasts, analysts will appear to exhibit overoptimism associated with abnormal accruals. Second, analysts may naively or irrationally believe that the abnormally high (or low) earnings may be as persistent as normal earnings.

I analyze the differential impact of normal and abnormal accruals to test for the possibility that analysts in particular are affected by abnormal accruals when setting their

future earnings expectations. Consequently, Hypothesis 3 predicts that forecast errors are more strongly associated with the abnormal accrual component of earnings:

Hypothesis 3: Prior period accruals are negatively associated with analysts' forecast errors predominantly due to the abnormal component of those accruals.

Support for Hypothesis 3 would also indicate the similarity between the forecasting process used by financial analysts and market participants, as shown in Xie [2001, forthcoming]. Thus the results in this study could serve as a motivation for further research regarding the nature of the accrual mispricing anomaly using the interaction between financial analysts' forecasts and market returns.

3.4.3 The Impact of Analyst Following on Forecast Efficiency with Respect to Accruals

The link between analyst following and the accrual efficiency of consensus forecasts is based on the assumptions and predictions of the naïve investor hypothesis. According to this hypothesis, there are differences in sophistication between investors, where less-sophisticated investors inefficiently process accrual information in earnings. This in effect results in incorrect earnings expectations on the part of these investors. A parallel argument could be made with respect to financial analysts, where high-quality analysts may be better at incorporating information about accruals into their forecasts than low-quality analysts. If this is the case then there are two reasons for the improvements in accrual efficiency when there is an increased number of analysts following a company:

(1) Low-quality analysts can observe the signals in forecasts issued by the high-quality analyst(s), with the resulting consensus forecast being more efficient with respect to accruals when one or more high-quality analysts follows a company.

(2) Larger analyst following should also impact accrual inefficiency in consensus forecasts in that decreasing weight is given to each analyst's forecast. As a result the amount of influence of a particular analyst's characteristics, beliefs, and private information is lessened in the consensus number (Kim, Lim, and Shaw [2000]). According to the naïve investor hypothesis, as the influence of individual characteristics (such as tendency to systematically overestimate the persistence of accruals) is lessened, the extent of accrual mispricing should decrease as well.

If, contrary to the expectations of the naïve investor hypothesis, all analysts are equally inefficient with respect to accruals, the number of analysts following a given company should not impact the extent of accrual inefficiency observed in the consensus forecast. Consequently, if accrual mispricing is characterized as a fixed bias common to all analysts, the extent of accrual bias should not diminish regardless of the level of aggregation in the consensus forecast.

Testing the influence of analyst following on accrual inefficiency in consensus forecasts provides indirect evidence for the naïve investor hypotheses. If the naïve investor hypothesis in fact explains the inefficiency in pricing accruals we should observe improvements in forecast efficiency with increases in analyst following. Hypothesis 4 tests that prediction:

Hypothesis 4: Consensus forecasts are more efficient with respect to prior accruals as the number of analysts following the firm increases.

Evidence presented by Ali *et al.* [2000] suggests that overall analyst following does not impact the level of abnormal returns associated with accrual mispricing, which implies that even stocks followed by more analysts exhibit anomalous returns. Testing of Hypothesis 4 gives evidence to answer whether the findings of Ali *et al.* [2000] are due to the lack of improvement in the forecast themselves or whether it is investors who do not take advantage of the information in improved consensus forecasts of stocks that are followed by more analysts.

3.4.4 The Relationship between Analyst Quality and the Propensity to Misprice Accruals

Using analyst forecast data to address the viability of the naïve investor hypothesis requires rejection of the view of financial analysts as a homogenous group. A relationship is sought between analysts' forecasting ability and their track records regarding the incorporation of differential persistence of accruals into their forecasts. I examine forecasts by individual analysts and focus on systematic, cross-sectional differences between analysts with respect to accrual mispricing in their forecast and their overall quality as analysts. The correlation, or lack thereof, between analysts' forecasting ability and accrual mispricing gives us an indication whether accruals are misinterpreted even by the most skilled analysts or whether superior analysts are able to issue forecasts that are efficient with respect to accounting accruals. Hypothesis 5 tests the expectation

of the naïve investor hypothesis that higher-quality, more sophisticated investors exhibit less accrual pricing inefficiency:

Hypothesis 5: Analysts' ability to recognize the differential persistence of accounting accruals is positively related to their forecasting ability.

Support for Hypothesis 5 would indicate that while on average analysts may not be efficient, those with better forecasting ability are more likely to recognize the differential persistence of earnings components. Such a result would be consistent with the existence of considerable heterogeneity in a class of informed investors, which is not captured by aggregate proxies for investor sophistication. If that is the case, the naïve investor hypothesis cannot be ruled out as the underlying cause of abnormal market returns. I investigate for patterns of different responses to normal and abnormal accruals that would indicate the specific difficulty of pricing the abnormal components of accrual compared to the normal component.

3.5 Summary

Given the evidence in literature regarding accrual mispricing and its causes, there are two main hypotheses that could explain the observed anomalous returns associated with accounting accruals. Influence of unaccounted risk factors is the default explanation, as the existence of the abnormal returns could be caused by inadequate research methodology and thus the alleged anomaly is purely an artifact of omitting the unknown risk factors. The naïve investor hypothesis is the alternative explanation,

according to which accrual mispricing occurs due to unsophisticated investors' tendency to assign higher persistence to the accrual component of earnings without regard to the accruals' lower persistence as compared to the persistence of cash flows. This study empirically tests research hypotheses designed to provide evidence that could lend support to either of the hypotheses. I test predictions of the naïve investor hypothesis in the realm of earnings forecasts. By doing so I am able to explicitly examine the link between the forecasting ability of market participants and their efficiency with respect to accruals, a connection that is central to the naïve investor hypothesis. Results of these tests and their implications for our understanding of the causes of accrual mispricing are presented in the next chapter.

CHAPTER 4 – EMPIRICAL MODELS, SAMPLE SELECTION AND RESULTS

4.1 Empirical Method

This study uses regression analysis to detect cross sectional patterns in analysts' responses to accounting accruals where I use forecast error as the dependent variable. Hypothesis testing relies on the sign, magnitude, and statistical significance of the regression coefficients. No complete model of analysts' forecast errors is currently available in the literature. Specification of the models could most likely be improved with proprietary data on analysts' names and their alignment with brokerage/investment banks and other financial institutions represented in the I/B/E/S database. Such data unfortunately is not available for academic use.

4.2 Models, Empirical Proxies and Variable Definitions

4.2.1 Dependent Variable Specification

Analyst forecast error is the cornerstone of this study and serves as the dependent variable in all regression equations. Analyst forecast error is defined as the difference between the actual earnings per share and the forecasted EPS as reported by I/B/E/S:

$$FE_{i,t,m} = ActualEPS_{i,t,m} - Forecast_{i,t,m}$$

Forecast error is based on the median of all outstanding forecasts for each company consensus sample and on each individual forecast in the detailed sample. The forecast error is scaled by the absolute value of EPS found in I/B/E/S. Accordingly, forecast error is measured as a percentage of reported earnings. Some authors use stock price at some point prior to earnings announcement as a scaling factor. This can possibly introduce bias into the study due to volatility of stock prices around earnings announcements. In this study, actual EPS is used as a less noisy and less arbitrary scaling factor compared to stock price.

4.2.2 Measures of Accruals

Three different measures of accruals are used in the study. There are two versions of working capital accruals, one based on Bradshaw *et al.* [forthcoming] and the other based on Sloan [1996]. The third accrual measure, total accruals, is also based on the definition in Bradshaw *et al.* Working capital accruals (BRS – Bradshaw, Richardson, and Sloan) are defined as:

$$\begin{aligned} \text{WCAcc(BRS)} = & \text{Increase in Accounts Receivable (Compustat \#302)} \\ & + \text{Increase in Inventory (Compustat \#303)} \\ & + \text{Decrease in Accts Payable and Accrued Liabilities (Compustat \#304)} \\ & + \text{Decrease in Accrued Income Taxes (Compustat \#305)} \\ & + \text{Increase (Decrease) in Other Assets (Liabilities) (Compustat \#307)} \end{aligned}$$

I also use Sloan's version of working capital accruals to provide a platform for comparison to earlier studies and ensure that results are not sensitive to accrual variable specification. Working capital accruals (Sloan) are defined as:

$$\text{WCAccS} = (\Delta\text{CA} - \Delta\text{Cash}) - (\Delta\text{CL} - \Delta\text{STD} - \Delta\text{TP}) - \text{Dep}$$

where ΔCA = change in current assets (Compustat item #4)
 ΔCash = change in cash/cash equivalents (Compustat item #1)
 ΔCL = change in current liabilities (Compustat item #5)
 ΔSTD = change in debt included in current liabilities (Compustat item #34)
 ΔTP = change in taxes payable (Compustat item #71)
 Dep = depreciation and amortization expense (Compustat item #14)

Total accruals are expected to be mispriced less by the market and analysts due to their steady, predictable components such as depreciation and amortization charges. Total accruals are defined as the difference between reported income before extraordinary items (Compustat item #123) and net cash flow from operating activities (Compustat item #308):

$$\text{TAcc} = \text{Income Before Extraordinary Items} - \text{Net Cash Flows from Operating Activities}$$

The Total Accruals Variable (TAcc) is identical to the one employed in Subramanyam [1996]. For consistency, the normal and abnormal accrual partitioning mechanism is also identical to the one Subramanyam uses. Based on total accruals (TAcc), the following

model is run separately for each two-digit SIC industry group with at least six firm-year observations in each industry group:

$$TAcc_{j,t} / TA_{j,t-1} = \alpha \cdot [1 / TA_{j,t-1}] + \beta \cdot [\Delta REV_{j,t} / TA_{j,t-1}] + \gamma [PPE_{j,t} / TA_{j,t-1}] + e_{j,t}$$

where: $TAcc$ = Accruals (Compustat Item #18 – Item #308)

ΔREV = Change in revenues (Compustat Item #12)

PPE = Property, Plant, and Equipment (Compustat Item #7)

TA = Total Assets (Compustat Item #6)

Following Sloan [1996] and Bradshaw *et al.* [forthcoming], accrual measures are scaled by average Total Assets (Compustat item #6). I perform my analysis using the actual values of accruals as well as decile rankings.

4.2.3 Individual Analyst Forecasting Ability

Present literature offers several methods of assessing analysts' ability, but we are far from having a standard, widely accepted ranking methodology (Sinha, Brown and Das [1998], Park and Stice [2000]). Other than using specialty or popular business magazine rankings, the measure of individual forecasting ability is usually based on forecast errors generated by a particular analyst. A primary concern for all inferences in this study regarding analyst ability and accrual inefficiency is the possibility that introducing a measure of forecasting ability based on historical forecast errors could induce circularity. This circularity would arise if analysts' misinterpretation of accruals were a strong determinant of forecast errors. This is not the case however. The explanatory power of

the accrual variable with respect to forecast errors is rather small, marking it as unlikely that an analyst would be classified as a superior among peers solely because he or she is better at pricing accruals.

In order to establish a yardstick for analysts' ability, I measure the accuracy of their forecasts relative to the consensus forecast, and I tabulate the frequency with which their forecasts are superior to the consensus forecast. I use the forecasts in the three months following the announcement of prior year's earnings in the tabulation and ranking, ensuring that analyst's interpretation of the accounting information from the prior period's financial results constitutes a relatively major portion of their forecast. Individual analysts' forecast is compared to the consensus forecast in that three-month period and the average rate of issuing superior forecasts (with smaller forecast error than the consensus forecast) is computed for each analyst. Firms followed by less than three analysts are not used in the computation of forecasting ability. The analysts are classified as Low Ability if their forecast is superior to the consensus forecast less than 30 percent of the time, and High Ability if their forecasts are more accurate than the consensus forecast 70 percent of the time. The remaining analysts are classified as Average. Analysts classification is fixed and does not change over time. To be included in the final sample, an analyst must have at least 30 forecasts available in the sample.

4.2.4 Control Variables

According to Brown [2000], the most important control variable in regressions using analysts' forecast errors is the forecast age. In this study, forecast age is controlled for by means of either using separate estimates for each month preceding the earnings announcement or, in case of aggregate regression specifications, the forecast horizon is used as a control variable.

Analyst following is also controlled, as the number of analysts following a given company possibly impacts the way the company discloses the information to the analysts. Moreover, as the analyst following increases, there is a greater possibility of analysts mimicking one another's forecasts. *AnalystFollowing* is used in all multivariate specifications as a control variable. Along with *AnalystFollowing*, the *Size* variable is also an important determinant of forecast errors since size itself is an important determinant of the information environment, which should have an effect on analyst performance and management behavior.

4.3 Sample Selection

The sample used in this study is based on available Compustat and I/B/E/S data for years 1988 through 1999. The Compustat sample consists of firm-years within Primary, Secondary, Tertiary, Research, and Full database files with available cash flow and accrual information for current and prior years sufficient for computation of accruals according to at least one of the definitions. This data requirement results in a sample size of 105,012 firm-year observations. I remove from the sample observations with scaled accruals exceeding total assets by a factor of three or more. This also resulted in the

removal of less than 1 percent of outliers in each accrual category. After calculating normal and abnormal components of accruals, I reduce the final size of the accrual sample to 103,392 firm-year observations.

The accrual sample was merged with the corresponding analysts' consensus forecast from the Aggregate I/B/E/S file. The initial number of post-1987 consensus forecasts of next year's earnings is 629,253. Merging the I/B/E/S sample data with Compustat accrual sample yielded 451,785 observations. Eliminating the extreme 1 percent of forecast errors and forecasts issued over a year before the current year's earnings announcement data sets resulted in the final consensus forecast sample size of 435,672.

The detailed analyst forecast sample is based on the I/B/E/S detail file, which lists earnings forecasts for each analyst, allowing for comparisons of earnings forecasts of individual analysts. The I/B/E/S Detail file consists of the total of 1,245,727 individual forecasts of year-ahead earnings. Elimination of forecasts issued over 12 months before the earnings announcement and the requirement to compute earnings surprises reduced the sample size to 1,026,833 individual forecasts. Merging with the accrual sample and the elimination of the extreme 1 percent of forecast errors reduced the sample size to 659,671. The extreme 1 percent of observations is due to I/B/E/S database errors, which result in anomalous values of forecast errors and also due to the use of EPS scaling factor which results in extreme outliers if the reported EPS in the sample were extremely small (1 cent or less). I subsequently compute mean forecast per analyst, per firm-year in order

to replace multiple forecasts for each firm-year-analyst combination. The mean forecast error computation results in the final sample size of 184,555.

4.3.1 Descriptive Statistics

There are two analyst forecast samples, one based on I/B/E/S consensus forecasts and the other based on the detailed individual forecast data. I use the consensus sample to test Hypotheses 1, 2, 3, and 4. Several factors limit sample size, most notably the availability of accounting information to compute accounting accruals; but also the lack of sufficient data to establish analyst ability for the detail sample. In each test I use the least constrained sample available, *i.e.*, testing of Hypothesis 1 is performed on a larger sample than tests of Hypothesis 5, which requires a measure of analysts' forecasting ability. Descriptive statistics in Table 1 show that the research samples used in this study reveal characteristics consistent with the prior research. Mean and median forecast errors are negative reflecting the tendency of analysts to be overoptimistic. The mean forecast error is substantially more negative than the median, which reflects a negatively skewed distribution of forecast errors. On average, each firm is followed by four analysts. A comparison of average total assets reveals that the sample consists of a large number of smaller firms.

I use the detailed sample to test Hypothesis 5, *i.e.*, whether there exists a negative correlation between individual analysts' forecasting ability and the extent of accrual inefficiency in their forecasts. This sample contains measures of individual analysts' forecasting ability derived from the data in the detailed I/B/E/S sample. The mean

forecast error is used in place of multiple forecasts errors for each analyst-firm-year in order to avoid serial correlation problems in regression estimation. The mean age of earnings forecasts used in the computation of mean forecast error is nine months.

An analysis of Table 2 indicates that the alternative accrual specifications are highly correlated, with correlation coefficients ranging from 0.50 to 0.75. Low persistence of accruals is evident with the correlation coefficient between current and prior period accruals ranging from 0.22 for WC Accruals to 0.28 for Total Accruals, compared with the persistence of cash flows, which is approximately 0.70 regardless of specification. As expected, abnormal accruals have the lowest persistence at 0.15.

4.4 Empirical Models

4.4.1 Hypotheses 1 and 2: Are Analysts Inefficient with Respect to Accruals?

A test of analyst inefficiency with respect to accruals relies on regression models with forecast error (*FE*) as a dependent variable and accounting accruals (*Accruals*) as an independent variable. A significant coefficient on the *Accruals* variable indicates that analysts' errors are systematically correlated with accruals. To test Hypothesis 1 which predicts accrual inefficiency in consensus forecasts, I use the following models:

$$FE_{i,t} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta Accruals_{i,t-1} + e_{i,t} \quad (1)$$

$$FE_{i,t} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 Accruals_{i,t-1} + \beta_2 CashFlows + e_{i,t} \quad (2)$$

In addition to the Accruals variable, model (1) includes *Industry* and *Year* control variables, while model (2) adds a *CashFlows* variable for the purpose of testing whether there is statistically significant difference between the coefficients of the two earnings components.

Since the forecast horizon has substantial influence on forecast errors (Brown [2000], Darrough and Russel [2000], Richardson, Teoh and Wysocki [2000]), both models are run separately for each month during the 11-month period from the prior year's ($t-1$) earnings announcement date to the month prior to the earnings announcement for year t . If analysts do not efficiently value the accrual component of earnings, we can expect gradually diminishing, negative coefficients on the prior year's accrual portfolios. Dummy control variables include *Industry* for each of the 15 industry groups and *Year* for each year in the sample data (1988-1999).

Table 3 shows coefficient estimates for model (1). The coefficients are negative for all accrual variable specifications, which indicates that analysts are overoptimistic in their assessment of total accrual persistence. As the earnings announcement date nears, the magnitude of the coefficient on accounting accruals diminishes. The coefficient on working capital accruals ranges from -0.6716 (-0.0509 in decile portfolio specification) to -0.1315 (-0.0118), showing similar tendency to diminish with the forecast horizon. The coefficients on Sloan's working capital accruals range from -0.474 to -0.0859 using actual values and from -0.03 to -0.005 using decile classification. Total Accruals are steadier and contain long term depreciation and amortization charges, changes that are more transparent and easier to predict. This predictability of long-term accruals

manifests itself in smaller coefficients in Total Accruals specifications ranging from -0.3828 to -0.0648. Figure 1 provides a comparison of coefficient magnitudes across forecast horizons for Working Accruals, Working Accruals (Sloan) and Total Accruals. When comparing the difference in coefficients between models using working capital accruals and total accruals, it is evident that, consistent with Hypothesis 2, working accruals pose significantly greater difficulty to financial analysts than do total accruals. Similar results are evident in Figure 2, which uses data from decile portfolio specifications.

Table 4 is presents estimations of coefficients on prior period accruals estimated in conjunction with the cash flow component of earnings using model (2). It is evident that just as analysts overestimate the persistence of accruals they underestimate the persistence of cash flows. This result is consistent with results in Sloan [1996] and Bradshaw *et al.* [forthcoming], both obtained using market data. Figure 3 contains a comparison of coefficient magnitudes using this specification. The overall pattern of analyst inefficiency is similar to that obtained with the model excluding cash flow variable, with a more pronounced difference between the working capital accruals (BRS) coefficient and the working accruals (Sloan) coefficient.³

The test results from Hypotheses 1 and 2 show a pattern of inefficiency with respect to the accrual component of earnings. These results are not sensitive to the choice of the forecast error variable specification (based on mean or median forecast) or to

³ Collins and Hribar [1999] demonstrate that the Sloan [1996] definition of working capital accruals may contain considerable error, which could explain why in this case, after controlling for cash flows, the coefficients on the working accruals (Sloan) would be closer to the coefficients on total accruals.

whether relative decile accrual portfolio rankings are substituted for actual accrual numbers. Predictably, the coefficients on total accruals are smaller from those on working capital accruals. Observed analyst inefficiency diminishes with time and is less pronounced (as indicated by both the coefficient size and R^2 values) in the months immediately preceding the earnings announcement. As noted in Bradshaw *et al.* [1999], this is most likely attributable to analysts' gradual acquisition of information from other sources and their decreased reliance on the previous periods' accounting data in constructing their forecasts as time progresses.

4.4.2 Hypothesis 3: Analysts' Response to Normal and Abnormal Components of Accruals

To gain further understanding of the analyst inefficiency observed in the results above, according to the prediction in Hypothesis 3, we should expect to observe accrual inefficiency mostly due to the abnormal component of accruals. I test this prediction using models analogous to those used for testing Hypotheses 1 and 2, but with an unconstrained coefficient on *Accruals* variable, that is, with separate normal and abnormal accrual variables:

$$FE_{i,t} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 NormalAccruals_{i,t-1} + \beta_2 AbnormalAccruals_{i,t-1} + e_{i,t} \quad (3)$$

$$\begin{aligned}
 FE_{i,t} = & \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_0 CashFlows + \\
 & + \beta_1 NormalAccruals_{i,t-1} + \beta_2 AbnormalAccruals_{i,t-1} + e_{i,t}
 \end{aligned}
 \tag{4}$$

Model (4) adds a *CashFlows* variable to model (3). If abnormal accruals are those primarily misinterpreted by financial analysts, as predicted in Hypothesis 3, the coefficient on *Abnormal Accruals* is expected to be more negative than the coefficient on *Normal Accruals*, i.e. $\beta_1 > \beta_2$.

Table 5 presents the results from testing Hypothesis 3 using both models. As expected, the coefficients on abnormal accruals are significantly larger than those on normal accruals. The results in Table 4 show that, in fact, the coefficient on normal accruals is often not significantly different from zero in all but the longest forecast horizon. The difference between the coefficients on normal and abnormal accruals is statistically significant in months 11 to 6 using the F-test. Figures 4 and 5 is a comparison of both coefficients. They provide a striking relief on the differential impact of normal and abnormal accruals on the efficiency of analysts' forecasts. Since abnormal accruals have lower persistence compared to the normal accruals, the fact that it is primarily the abnormal accruals, the least persistent component of earnings, which are misinterpreted by the analysts, is indicative of analysts' tendency to overestimate the persistence of earnings without regard to earnings components and their persistence. Such propensity to overestimate the persistence of accruals may either arise from inefficient forecasting techniques, susceptibility to being misled by management teams, or a combination of both. This result further underscores the propensity among market

participants to overestimate the persistence of transitory earnings components, corroborating the results of Xie [2001, forthcoming].

4.4.3 Hypothesis 4: The Effect of Analyst Following on Efficiency of Consensus Forecasts with Respect to Accruals

Hypothesis 4 focuses on the implications of analyst following for the efficiency of consensus forecasts and seeks to establish a link between analyst following and the extent of accrual inefficiency in consensus forecast. Larger analyst following reflects consensus forecast that is a median of a larger number of forecasts, increasing the likelihood that one or more high quality analysts are following a given company. Hypothesis 4 predicts that if high quality analysts are better at incorporating the true persistence of accruals into their forecasts, the accuracy of the consensus forecast will improve. Testing of Hypothesis 4 focuses on the interaction term between the number of analysts and prior period's accruals in the following model:

$$\begin{aligned}
 FE_{i,t,j} = & \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlow_{i,t-1} + \beta_2 Accruals_{i,t-1} + \\
 & + \beta_4 AnalystFollowing_{i,t,j} + \beta_3 Accruals_{i,t-1} \cdot AnalystFollowing_{i,t,j} + \quad (4) \\
 & + \beta_5 ForecastHorizon_{i,t,j} + \beta_6 Size_{i,t} + \beta_6 Accruals_{i,t-1} \cdot Size_{i,t} + e_{i,t,j}
 \end{aligned}$$

As with models 1 and 2, this model is run separately for each month during the 11-month period from the prior year's ($t-1$) earnings announcement date prior to the earnings announcement for year t . The *Size* variable (average total assets) and its

interaction with *Accruals* are included to control for scale effect and to ensure that the effect of increased analyst following is properly isolated given that larger firms tend to be followed by a greater number of analysts. The expected sign on β_5 , the coefficient on the *Size* variable, is positive as analysts are expected to be less overoptimistic with larger firms. Consistent with accrual mispricing, a negative sign is expected for β_2 . According to Hypothesis 4, the sign on the interaction between *Accruals* and *Analyst Following* (β_3) should be positive, which is the opposite of the negative sign of the coefficient on accruals (β_2).

The results are reported in Table 6. The significant positive coefficient on the interaction term indicates that as the number of analysts increases so does the extent of accrual mispricing is present in the overall consensus forecasts. In other words, when a larger number of analysts follows a firm, the consensus forecast is more likely to include forecasts made by high-quality analysts and thus decreased accrual inefficiency is expected. Panel A of Table 6, which uses working capital accruals, the interaction coefficient is significantly positive in all but the longest horizon, ranging from the maximum of 0.046 to the minimum of 0.020 and representing approximately 10 to 15 percent of the magnitude of the coefficient on accruals, depending on the forecast horizon. Panel B, which uses the alternative working accruals specification, shows the interaction coefficient to be significantly positive in all but the shortest horizon. The magnitude of the coefficient ranges from 5 to 11 percent of the coefficient on accruals. Based on the coefficient, it appears that companies that are followed by more analysts experience a significant reduction in accrual bias in the consensus forecasts of their

earnings. On average, the consensus forecast for firms followed by four analysts (the average in the sample) would experience a reduction of 20 to 40 percent in the extent of its accrual bias.

Panel C of Table 6 presents the results of estimation using the total accruals specification. The impact of analyst following is smaller compared to the estimation results using working accruals. The interaction variable is significant in forecast horizons of seven to three months. Also, the magnitude of the coefficient is smaller, reaching only up to 5 percent of the magnitude of the coefficient on *Total Accruals*. Given that the accrual inefficiency is primarily concentrated on working capital accruals, these results are not surprising.

I also use an alternative, cross-sectional specification pooled over time to test Hypothesis 4. Unlike the partitioned model (4), pooled cross-sectional regression provides for a stronger test of Hypothesis 4, at the cost of potentially introducing a serial correlation bias resulting from using multiple consensus forecasts available in each year for each firm. Model (5) is specified as follows:

$$\begin{aligned}
 FE_{i,t,j} = & \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlow_{i,t-1} + \beta_2 Accruals_{i,t-1} + \\
 & + \beta_4 AnalystFollowing_{i,t,j} + \beta_3 Accruals_{i,t-1} \cdot AnalystFollowing_{i,t,j} + \quad (5) \\
 & + \beta_5 ForecastHorizon_{i,t,j} + \beta_6 Size_{i,t} + \beta_6 Accruals_{i,t-1} \cdot Size_{i,t} + e_{i,t,j}
 \end{aligned}$$

As in the models using separate month-by-month specification, the coefficient on the interaction between *Accruals* and *Analyst Following* (β_3) should be positive, the opposite

of the negative sign of the coefficient on accruals (β_2). The results in Table 7 show that coefficient β_2 is positive and statistically significant across all specifications. Results in parentheses refer to estimation using decile assignments based on the magnitude of accruals. Panel A shows that for working capital specification, the coefficient on accruals, $\beta_2 = -0.939$ (-0.036) and, the interaction coefficient, $\beta_3 = 0.0376$ (0.0017). Using Sloan's [1996] definition of working capital accruals, $\beta_2 = -0.621$ (-0.026) and $\beta_3 = 0.039$ (0.0016). Panel C presents the results for estimation using the total accruals, yielding $\beta_2 = -0.4147$ (-0.027) and $\beta_3 = 0.0199$ (0.0016). The coefficient on accruals and the interaction variable in the estimation using total accruals compared to working capital specifications is similar to the results obtained from month-by-month specification.

Overall, the results show that analyst following does seem to alleviate the extent of accrual inefficiency among financial analysts, suggesting that the efficiency with respect to accruals improves with the participation of high-quality analysts as well as the diffusion of noise in individual forecasts. The fact that the accrual inefficiency diminishes as the overall quality of a consensus forecast increases seems to validate the prediction of the naïve investor hypothesis claiming that better forecasting methods can in fact alleviate the extent of accrual mispricing.

4.4.4 Hypothesis 5: The Impact of Analyst's Relative Forecasting Ability on their Propensity to Misprice Accruals

I directly test the predictions of the naïve investors hypothesis by examining the relationship between analyst sophistication and their propensity to misprice accruals.

Hypothesis 5 predicts that higher quality analysts are less likely to overestimate the persistence of accruals. The testing of my hypothesis is based on a comparison of the responses of analysts to accrual information depending on their level of forecasting ability. The following regression model is used to test Hypothesis 5:

$$\begin{aligned}
 FE_{i,t,j} = & \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlows_{i,t-1} + \\
 & + \beta_{2H} HAbility \cdot Accruals_{i,t-1} + \\
 & + \beta_{2M} MAbility \cdot Accruals_{i,t-1} + \\
 & + \beta_{2L} LAbility \cdot Accruals_{i,t-1} + \\
 & + \beta_3 Ability + \beta_4 MeanHorizon + \beta_5 AnalystFollowing_{i,t,j} + \beta_6 Size_{i,t} + e_{i,t,j}
 \end{aligned} \tag{5}$$

Variable *HAbility* is assigned a value of one for the high ability analysts, and zero otherwise; similarly *MAbility* equals one for medium ability analysts and zero otherwise; while *LAbility* is set to one for low ability analysts and zero otherwise. According to Hypothesis 5, if better analysts are indeed better at pricing accruals the coefficient β_{2H} should be larger (less negative) than either coefficients β_{2M} or β_{2L} . The magnitude of β_{2L} should analogously exceed both β_{2H} and β_{2M} . The *Size* variable (average total assets) is included to control for any potential influence on the forecast error of a given company's size or risk class. *Analyst Following* controls for the likelihood that a particular analyst issues better forecasts simply by observing other analysts' forecasts, and, as in the regression models above, it controls for institutional differences that may be associated with the extent of analyst following. *MeanHorizon* controls for the average age of the forecasts used in computing the mean forecast error.

Table 8 reports the results from testing Hypothesis 5. Panel A shows the estimation of model (5) using the working capital accruals. The coefficients on accrual efficiency show substantial variance across different ability groups: the high-ability group's coefficient is the least negative at -0.4355 (-0.0175). The medium-ability analysts' coefficient is slightly more negative at -0.5087 (-0.0455) and highly significant. Low-ability analysts seem to have the most significant margin of difficulty with pricing accruals, exhibiting a highly negative coefficient of -2.6033 (-0.1410). Numbers in parentheses refer to the decile specification, where the differences between ability groups are even more significant. Overall an F-test rejects the equality of the coefficients at confidence levels exceeding 1 percent, except the difference between high and medium ability groups using actual values specification is insignificant.

Panel B of Table 8 provides results using Sloan's [1996] version of working capital accruals. The results are very similar to those in Panel A. Again, there is a pronounced difference in coefficients among different ability groups. Except for the difference between the high- and medium-ability groups, all the differences are significant according to the F-test.

Panel C contains the results of estimation using total accruals. As was the case with the previous two specifications, the differences between coefficients are statistically significant according to the F-test, albeit at 5 and 10 percentage levels. The coefficients on accruals is not statistically different from zero for the high-ability group whereas it is significant at 5 and 1 percentage levels for medium- and low-ability groups.

Given the evidence of abnormal accruals as the main factor in accrual inefficiency, a modified version of model (5) is used to test Hypothesis 5 using the normal/abnormal accruals partitioning:

$$\begin{aligned}
 MFE_{i,j} = & \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlows_{i,j-1} + \\
 & + \beta_{2H} HAbility_i \cdot NAccruals_{i,j-1} + \beta_{2M} MAbility_i \cdot NAccruals_{i,j-1} + \beta_{2L} LAbility_i \cdot NAccruals_{i,j-1} + \\
 & + \beta_{3H} HAbility_i \cdot AbAccruals_{i,j-1} + \beta_{3M} MAbility_i \cdot AbAccruals_{i,j-1} + \beta_{3L} LAbility_i \cdot AbAccruals_{i,j-1} + \\
 & + \beta_4 Ability + \beta_5 MeanHorizon + \beta_6 AnalystFollowing_{i,j} + \beta_7 Size_{i,j} + e_{i,j}
 \end{aligned} \tag{6}$$

This specification allows us to compare the differences in the patterns of accrual forecasting efficiency not only by analyst ability but simultaneously by analyst ability and the types of accrual. It is expected that as in the test of Hypothesis 3, the coefficients on abnormal accruals will be more negative compared to the coefficients on normal accruals for Hypothesis 5.

Table 9 presents the results of estimating model (6). In the case of normal accruals, there are significant differences between the coefficients according to the F-test, however, only the coefficient on the low-ability group is significant at a level of 10 percent. The results seem to suggest that while differences exist between the groups, the level of mispricing of normal accruals is low. This is not the case with the abnormal accruals. Here, as expected, the analysts have more difficulty, regardless of their ability levels. The coefficients on abnormal accruals for the medium and low ability groups are significant at 1% level. An F-test does not indicate statistically significant differences among the coefficients due to relatively high variances of each estimator. This is

possibly due to normal and abnormal accruals' basing on total accruals, the weakest indicator of mispricing, and possibly due to imperfections in the cross-sectional, industry-level Jones model partitioning of accruals. Nevertheless, the results are consistent with the expectations that abnormal accruals are more challenging to analysts regardless of their ability level and that while only low-ability analysts seem to have difficulty in pricing normal accruals, all groups seem to suffer from inefficiency with regard to firms with high levels of abnormal accruals.

CHAPTER 5 – SUMMARY AND CONCLUSIONS

Accrual mispricing provides a challenge to accounting researchers. It seems to show an inefficient or irrational behavior by financial market participants. In this study I use an indirect approach in my contributory response to the challenge by taking advantage of the unique characteristics of the cross-sectional and time-series data available on the earnings forecasts made by financial analysts. By using financial analysts to gain insight into the nature of the accrual mispricing anomaly I am able to determine whether forecasting ability influences the extent of accrual mispricing. With an affirmative answer in hand, this research offers additional evidence for the viability of the naïve investor hypothesis. The evidence is far from conclusive and the caveats abound when we consider the specificity of the financial analysts community and its institutional environment. After all, it is collectively all market participants, not just financial analysts as a subgroup, whose erroneous earnings expectations seem to cause the abnormal returns associated with the anomaly. Nevertheless, the evidence suggests that financial analysts suffer from a form of inefficiency that is consistent with the abnormal returns observed in the market, and thus it is likely that the results of this study can provide some insight into the behavior of investors in general. These results provide evidence regarding the financial analysts' responses to accounting accruals and confirm their inability to fully incorporate the implications of prior period accruals for current period earnings. Consistent with the predictions of the naïve investor hypothesis, the level of accrual mispricing is shown to vary from analyst to analyst. In support of the

main preposition of the naïve investor hypothesis, I show analysts' quality as correlated with their forecasting efficiency with respect to prior accruals. According to the results, average-quality analysts correctly assess the persistence of normal accruals, but even high-quality analysts are likely to overestimate the persistence of abnormal accruals. The evidence in this paper highlights the viability of the naïve investor hypothesis as a possible explanation for the anomalous behavior of market participants, with higher-quality analysts being far more efficient in avoiding the forecast inefficiency associated with accounting accruals.

Future research is needed in exploring the nature of accrual mispricing. Primarily, examining the relation between accuracy of analysts' earnings forecasts and the abnormal returns associated with accrual mispricing could yield additional valuable evidence regarding the origins of the anomaly. Such research would combine the results in existing studies using market data and the results of this study, which concentrates on analysts' forecasts.

Continuing research is also needed in the area of reporting discretion and earnings manipulation, given that firms with high levels of abnormal accruals seem to be especially vulnerable to future substantial negative earnings surprises. The recent decrease in the overall quality of earnings warrants additional attention from the SEC. The situation is unlikely to improve when we consider the pressures on companies generated by the macroeconomic downturn and bear markets of today. It is incumbent upon researchers in accounting to provide substantial and unbiased evidence regarding the impact of accounting manipulation on market participants and whether the largely

benevolent view of managerial discretion in financial reporting in the accounting literature is fully justified. As evidenced by results found in the literature on accrual mispricing, investors have difficulty in pricing the accrual component and are not able to completely “see through” the managerial accounting discretion. As the results of this study support the naïve investor hypothesis as the explanation for the observed abnormal returns, it is likely that average, non-institutional investors might be misled by accounting numbers. Accounting information that is not straightforward and downright misleading to outsiders should be of a concern to the Security and Exchange Commission, which is responsible for maintaining a level playing field for all investors.

APPENDIX A - VARIABLE DEFINITIONS

$$\text{Forecast Error} = \frac{\text{ActualEPS}_{i,t} - \text{Forecast}_{i,t}}{|\text{ActualEPS}_{i,t}|}$$

Working Capital Accruals = Increase in Accounts Receivable
 + Increase in Inventory
 + Decrease in Accounts Payable and Accrued Liabilities
 + Decrease in Accrued Income Taxes
 + Increase (Decrease) in Assets (Liabilities) – Other

Working Capital Accruals (Sloan) = ($\Delta\text{CA} - \Delta\text{Cash}$) – ($\Delta\text{CL} - \Delta\text{STD} - \Delta\text{TP}$) – Dep

where ΔCA = change in current assets
 ΔCash = change in cash/cash equivalents
 ΔCL = change in current liabilities
 ΔSTD = change in debt included in current liabilities
 ΔTP = change in taxes payable
 Dep = depreciation and amortization expense

$$\text{Total Accruals} = \frac{\text{Income Before Extraordinary Items}_{i,t} - \text{Net Cash Flows from Operating Activities}_{i,t}}{\text{AverageTotalAssets}_{i,t}}$$

Analyst Following = number of analyst issuing earnings forecasts for a given stock.

Non-Discretionary and Discretionary Accruals are computed as the predicted value and the residual of the following Jones model specification with parameters of the model estimated separately for each two digit industry classification code group:

$$TAcc_{j,t} / TA_{j,t-1} = \alpha \cdot [1 / TA_{j,t-1}] + \beta \cdot [\Delta REV_{j,t} / TA_{j,t-1}] + \gamma [PPE_{j,t} / TA_{j,t-1}] + e_{j,t}$$

where: $TAcc$ = Accruals (Compustat Item #18 – Item #308)
 ΔREV = change in revenues (Compustat Item #12)
 PPE = Property, Plant, and Equipment (Compustat Item #7)
 TA = Total Assets (Compustat Item #6)

APPENDIX B - TABLES

LIST OF TABLES

Table 1. Descriptive Statistics.....	66
Table 2. Correlation Matrix.....	67
Table 3 Impact of prior period accruals on forecast errors	
Panel A: Working Capital Accruals	68
Panel B: Working Capital Accruals (Sloan).....	69
Panel C: Total Accruals	70
Table 4 Impact of prior period accruals and cash flows on forecast errors.....	71
Table 5 Differential impact of prior period normal and abnormal accruals on forecast errors	72
Table 6 Impact of analyst following on earnings forecast error and accrual inefficiency in consensus forecasts, by forecast horizon.	
Panel A: Working Capital Accruals	73
Panel B: Working Capital Accruals (Sloan)	74
Panel C: Total Accruals	75
Table 7 Impact of analyst following on earnings forecast error and accrual inefficiency in consensus forecasts (aggregate regression).	
Panel A: Working Capital Accruals	76
Panel B: Working Capital Accruals (Sloan)	77
Panel C: Total Accruals	78

LIST OF TABLES - *Continued*

Table 8	Impact of analyst following on earnings forecast error and accrual inefficiency in consensus forecasts	
	Panel A: Working Capital Accruals	79
	Panel B: Working capital accruals (Sloan)	80
	Panel C: Total Accruals	81
Table 9	Impact of analyst forecasting ability on the extent of accrual inefficiency in their forecasts: the case of normal vs. abnormal accruals.....	82

Table 1. Descriptive Statistics

Panel A: Aggregate earnings forecast sample						
	N	Mean	St. Deviation	Max	Median	Min
Forecast Error	451,785	-0.5176	1.4314	1.7010	-0.0353	-13.550
Working Capital Accruals	221,222	0.0273	0.0978	1.3293	0.0151	-2.3679
WC Accruals (Sloan)	395,410	-0.0299	0.1081	1.7672	-0.0354	-2.2975
Total Accruals	444,537	-0.0459	0.1288	1.5557	-0.0415	-3.9022
Abnormal Accruals	433,425	-0.0055	0.1202	1.6012	-0.0002	-3.7832
Normal Accruals	439,596	-0.0412	0.0542	0.5412	-0.0385	-1.0883
Analyst Following	451,785	6.9373	7.2354	51	4	1
Average Total Assets	449,283	2.1237	9.6312	508.329	0.2528	0.0553

Panel B: Individual earnings forecast sample						
	N	Mean	St. Deviation	Max	Median	Min
Mean Forecast Error (MFE)	184,555	-0.4142	1.0740	0.982	-0.0138	-9.5214
Mean Horizon	184,555	8.1112	3.0106	12	9	1
Analyst Ability	184,555	1.1099	0.5564	2	1	0
Working Capital Accruals	83,836	0.0314	0.1244	3.9553	-0.0424	-2.4566
WC Accruals (Sloan)	164,564	-0.0320	0.1268	3.9962	-0.0422	-3.6569
Total Accruals	181,284	-0.0500	0.1367	3.8541	-0.0497	-3.8203
Abnormal Accruals	177,904	-0.0075	0.1213	3.1362	-0.0029	-3.8416
Normal Accruals	180,529	-0.0431	0.0676	2.5399	-0.0425	-3.1095
Average Total Assets	184,068	5.6750	17.007	386.55	0.9841	0.0371

Table 2. Correlation Matrix

	Size _t	Analyst Following _t	WC Accrs _t	WC Accrs _t (Sloan)	Total Accrs _t	Normal Accrs _t	Abnormal Accrs _t	Cash Flows _t	Cash Flows _t (Sloan)	Total Cash Flows _t	WC Accrs _{t+1}	WC Accrs _{t+1} (Sloan)	Total Accrs _{t+1}	Abnormal Accrs _{t+1}	Normal Accrs _{t+1}	Cash Flows _{t+1}	CF _{t+1} (Sloan)	Total CF _{t+1}
Size _t	1	0.3888	-0.0250	-0.0333	-0.0104	-0.0017	-0.0233	0.0868	0.0942	0.0838	-0.0385	-0.0477	-0.0226	-0.0091	-0.0234	0.0828	0.0922	0.0800
Analyst Following _t	0.3888	1	-0.0643	-0.0616	-0.0278	-0.0066	-0.0517	0.2060	0.1925	0.1921	-0.0777	-0.0745	-0.0422	-0.0106	-0.0395	0.2004	0.1914	0.1861
WC Accruals _t	-0.0250	-0.0643	1	0.7524	0.7016	0.6225	0.3095	-0.2434	-0.1714	-0.2688	0.2267	0.1739	0.1628	0.0838	0.1240	0.0017	0.0131	-0.0274
WC Accruals _t (Sloan)	-0.0333	-0.0616	0.7524	1	0.6647	0.5261	0.4150	-0.1151	-0.2778	-0.1794	0.1564	0.2298	0.2078	0.0848	0.2102	0.0396	0.0120	-0.0113
Total Accruals _t	-0.0104	-0.0278	0.7016	0.6647	1	0.9080	0.3653	-0.0220	-0.0290	-0.1732	0.1546	0.2241	0.2854	0.1531	0.1879	0.1185	0.0836	0.0238
Normal Accruals _t	-0.0017	-0.0066	0.6225	0.5261	0.9080	1	-0.0585	-0.0136	-0.0117	-0.1422	0.0796	0.0955	0.1772	0.1564	-0.0070	0.1401	0.1202	0.0681
Abnormal Accruals _t	-0.0233	-0.0517	0.3095	0.4150	0.3653	-0.0585	1	-0.0207	-0.0313	-0.0825	0.2040	0.3230	0.2731	0.0171	0.4615	-0.0379	-0.0628	-0.0899
Cash Flows _t	0.0868	0.2060	-0.2434	-0.1151	-0.0220	-0.0136	-0.0207	1	0.9525	0.9479	-0.0151	0.0036	0.0885	0.0729	0.0040	0.7574	0.7372	0.7146
Cash Flows _t (Sloan)	0.0942	0.1925	-0.1714	-0.2778	-0.0290	-0.0117	-0.0313	0.9525	1	0.9086	0.0123	-0.0035	0.0729	0.0712	-0.0106	0.7357	0.7213	0.6975
Total Cash Flows _t	0.0838	0.1921	-0.2688	-0.1794	-0.1732	-0.1422	-0.0825	0.9479	0.9086	1	-0.0229	-0.0507	0.0085	0.0387	-0.0510	0.7230	0.7011	0.7109
WC Accruals _{t+1}	-0.0385	-0.0777	0.2267	0.1564	0.1546	0.0796	0.2040	-0.0151	0.0123	-0.0229	1	0.7474	0.7276	0.6418	0.3522	-0.2521	-0.1965	-0.2878
WC Accruals _{t+1} (Sloan)	-0.0477	-0.0745	0.1739	0.2298	0.2241	0.0955	0.3230	0.0036	-0.0035	-0.0307	0.7474	1	0.6839	0.5158	0.4067	-0.1569	-0.3056	-0.2025
Total Accruals _{t+1}	-0.0226	-0.0422	0.1628	0.2078	0.2854	0.1772	0.2731	0.0885	0.0729	0.0085	0.7276	0.6839	1	0.8973	0.3988	-0.0659	-0.0693	-0.1977
Abnormal Accruals _{t+1}	-0.0091	-0.0106	0.0838	0.0848	0.1531	0.1564	0.0171	0.0729	0.0712	0.0387	0.6418	0.5158	0.8973	1	-0.0388	-0.0719	-0.0676	-0.1805
Normal Accruals _{t+1}	-0.0234	-0.0395	0.1240	0.2102	0.1879	-0.0070	0.4615	0.0040	-0.0106	-0.0510	0.3522	0.4067	0.3988	-0.0388	1	-0.0335	-0.0573	-0.1009
Cash Flows _{t+1}	0.0828	0.2004	0.0017	0.0396	0.1185	0.1401	-0.0379	0.7574	0.7357	0.7230	-0.2521	-0.1569	-0.0659	-0.0719	-0.0335	1	0.9514	0.9556
Cash Flows _{t+1} (Sloan)	0.0922	0.1914	0.0131	0.0120	0.0836	0.1202	-0.0628	0.7372	0.7213	0.7011	-0.1965	-0.3056	-0.0693	-0.0676	-0.0573	0.9514	1	0.9097
Total Cash Flows _{t+1}	0.0800	0.1861	-0.0274	-0.0113	0.0238	0.0681	-0.0899	0.7146	0.6975	0.7109	-0.2878	-0.2025	-0.1977	-0.1805	-0.1009	0.9556	0.9097	1

Table 3. Impact of prior period accruals on forecast errors, by forecast horizon

Panel A: Working Capital Accruals

$$FE_{i,t} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta Accruals_{i,t-1} + e_{i,t}$$

Portfolio Assignments

Month	α	t-stat	β	t-stat	N	R-sq
1	-0.22765	-3.44	-0.01179	-3.12	8097	0.96%
2	-0.12439	-3.14	-0.01085	-4.09	17760	0.82%
3	-0.04498	-1.31	-0.01466	-5.42	18374	0.91%
4	-0.06732	-1.88	-0.01584	-5.45	18505	1.03%
5	-0.11238	-2.89	-0.02179	-6.86	18442	1.03%
6	-0.19808	-4.66	-0.02272	-6.51	18388	1.10%
7	-0.13915	-3.10	-0.03065	-8.31	18286	1.44%
8	-0.21144	-4.45	-0.03597	-9.23	18190	1.47%
9	-0.23420	-4.56	-0.04008	-9.59	18039	1.59%
10	-0.25711	-4.79	-0.04804	-11.01	17814	1.83%
11	-0.32118	-5.49	-0.05087	-10.74	17445	1.97%

Actual Values

Month	α	t-stat	β	t-stat	N	R-sq
1	-0.28324	-4.46	-0.13151	-2.54	8097	0.92%
2	-0.17289	-4.60	-0.15813	-4.19	17760	0.83%
3	-0.11098	-3.49	-0.20483	-5.31	18374	0.90%
4	-0.13798	-4.18	-0.21478	-5.26	18505	1.02%
5	-0.21084	-5.88	-0.28313	-6.33	18442	1.00%
6	-0.29944	-7.64	-0.34857	-7.04	18388	1.14%
7	-0.27528	-6.64	-0.46553	-9.02	18286	1.50%
8	-0.37066	-8.47	-0.50376	-9.21	18190	1.47%
9	-0.41055	-8.68	-0.56296	-9.48	18039	1.58%
10	-0.46450	-9.38	-0.66357	-10.52	17814	1.77%
11	-0.54148	-10.04	-0.67158	-9.71	17445	1.85%

Table 3 (cont.): Impact of prior period accruals on forecast errors, by forecast horizon

Panel B: Working Capital Accruals (Sloan)

$$FE_{i,t} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta Accruals_{i,t-1} + e_{i,t}$$

Portfolio Assignments

Month	α	t-stat	β	t-stat	N	R-sq
1	-0.24831	-7.36	-0.00484	-1.80	15,200	0.73%
2	-0.16040	-6.87	-0.00541	-2.86	33,000	0.59%
3	-0.12064	-5.29	-0.00877	-4.44	34,062	0.60%
4	-0.11990	-4.89	-0.01200	-5.57	34,312	0.72%
5	-0.16349	-6.12	-0.01680	-7.13	34,251	0.83%
6	-0.21235	-7.35	-0.01813	-7.10	34,161	0.90%
7	-0.22384	-7.32	-0.02017	-7.47	33,967	0.97%
8	-0.25846	-8.02	-0.02324	-8.15	33,807	1.11%
9	-0.27717	-8.01	-0.02582	-8.47	33,510	1.21%
10	-0.30934	-8.51	-0.03027	-9.44	33,147	1.36%
11	-0.37007	-9.42	-0.02997	-8.65	32,466	1.46%

Actual Values

Month	α	t-stat	β	t-stat	N	R-sq
1	-0.27461	-8.89	-0.08593	-2.20	15,200	0.74%
2	-0.19068	-8.88	-0.12316	-4.53	33,000	0.63%
3	-0.16877	-8.15	-0.15841	-5.58	34,062	0.63%
4	-0.18556	-8.35	-0.22238	-7.26	34,312	0.78%
5	-0.25464	-10.54	-0.28317	-8.42	34,251	0.88%
6	-0.31080	-11.91	-0.31895	-8.70	34,161	0.98%
7	-0.33304	-12.06	-0.35930	-9.23	33,967	1.06%
8	-0.38250	-13.13	-0.37598	-9.01	33,807	1.16%
9	-0.41493	-13.28	-0.43707	-9.67	33,510	1.27%
10	-0.47005	-14.33	-0.47843	-9.92	33,147	1.39%
11	-0.52863	-14.91	-0.47401	-9.02	32,466	1.48%

Table 3 (cont.): Impact of prior period accruals on forecast errors, by forecast horizon

Panel C: Total Accruals

$$FE_{i,t} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta Accruals_{i,t-1} + e_{i,t}$$

Portfolio Assignments

Month	α	t-stat	β	t-stat	N	R-sq
1	-0.18652	-4.07	-0.00809	-3.05	16,064	1.07%
2	-0.10719	-3.92	-0.00653	-3.50	35,335	0.99%
3	-0.06544	-2.72	-0.01089	-5.73	36,528	0.79%
4	-0.08758	-3.43	-0.01298	-6.26	36,820	0.91%
5	-0.14495	-5.26	-0.01873	-8.32	36,743	0.99%
6	-0.19084	-6.41	-0.01969	-8.07	36,641	1.00%
7	-0.20059	-6.39	-0.02029	-7.88	36,468	1.09%
8	-0.25473	-7.66	-0.02277	-8.34	36,295	1.20%
9	-0.29577	-8.28	-0.02465	-8.44	36,035	1.31%
10	-0.29607	-7.91	-0.03085	-10.07	35,663	1.49%
11	-0.35351	-8.74	-0.03207	-9.70	34,962	1.62%

Actual Values

Month	α	t-stat	β	t-stat	N	R-sq
1	-0.23041	-5.25	-0.06478	-1.80	16,064	1.04%
2	-0.14364	-5.49	-0.08217	-3.31	35,335	0.98%
3	-0.12564	-5.56	-0.12397	-4.92	36,528	0.77%
4	-0.16046	-6.70	-0.15344	-5.67	36,820	0.89%
5	-0.24874	-9.64	-0.20541	-6.94	36,743	0.93%
6	-0.30169	-10.82	-0.23591	-7.25	36,641	0.97%
7	-0.31641	-10.77	-0.26504	-7.76	36,468	1.09%
8	-0.38222	-12.29	-0.27681	-7.54	36,295	1.17%
9	-0.43194	-12.95	-0.28882	-7.27	36,035	1.26%
10	-0.46549	-13.32	-0.36574	-8.64	35,663	1.42%
11	-0.52972	-14.04	-0.38286	-8.28	34,962	1.55%

Table 4. Impact of prior period accruals on forecast errors, by forecast horizon.

$$FE_{i,t} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 Accruals_{i,t-1} + \beta_2 CashFlows + e_{i,t}$$

Working Capital Accruals

<i>Month</i>	α	t-stat	β_1	t-stat	β_2	t-stat	N	R-sq
1	-0.29478	-4.67	-0.11988	-2.05	0.09961	2.90	7995	0.91%
2	-0.18019	-4.76	-0.13704	-3.24	0.08381	3.44	17516	0.75%
3	-0.11369	-3.53	-0.17674	-4.07	0.07699	3.15	18123	0.84%
4	-0.13729	-4.12	-0.19592	-4.23	0.05698	2.18	18251	0.89%
5	-0.20856	-5.73	-0.25959	-5.10	0.08988	3.11	18197	1.00%
6	-0.30436	-7.64	-0.32474	-5.74	0.08046	2.51	18158	1.16%
7	-0.27325	-6.52	-0.41254	-6.96	0.10270	3.02	18041	1.45%
8	-0.36868	-8.30	-0.48229	-7.64	0.10695	2.95	17954	1.50%
9	-0.40975	-8.59	-0.52684	-7.73	0.13830	3.53	17801	1.63%
10	-0.45565	-9.13	-0.62989	-8.73	0.16194	3.87	17601	1.88%
11	-0.53111	-9.76	-0.64650	-8.15	0.20969	4.54	17236	2.03%

Working Capital Accruals (Sloan)

<i>Month</i>	α	t-stat	β_1	t-stat	β_2	t-stat	N	R-sq
1	-0.28461	-9.18	-0.02548	-0.59	0.12163	4.60	15160	0.87%
2	-0.19699	-9.13	-0.06389	-2.09	0.11603	6.09	32896	0.74%
3	-0.17314	-8.33	-0.10195	-3.20	0.11333	5.74	33958	0.72%
4	-0.18826	-8.44	-0.17599	-5.10	0.10442	4.84	34207	0.84%
5	-0.25832	-10.66	-0.22484	-5.93	0.14051	5.91	34152	0.98%
6	-0.31569	-12.06	-0.24638	-6.02	0.15161	5.85	34069	1.06%
7	-0.33683	-12.17	-0.25805	-5.91	0.18227	6.59	33875	1.15%
8	-0.38660	-13.24	-0.26843	-5.73	0.19741	6.67	33715	1.26%
9	-0.42085	-13.44	-0.31029	-6.12	0.22450	7.03	33423	1.38%
10	-0.47684	-14.52	-0.34132	-6.34	0.25038	7.30	33070	1.53%
11	-0.54198	-15.26	-0.32393	-5.52	0.31307	8.29	32391	1.69%

Total Accruals

<i>Month</i>	α	t-stat	β_1	t-stat	β_2	t-stat	N	R-sq
1	-0.23296	-5.30	-0.02501	-0.63	0.10926	3.86	16024	1.12%
2	-0.14382	-5.49	-0.05178	-1.92	0.11761	5.79	35257	1.08%
3	-0.12337	-5.44	-0.09434	-3.45	0.12171	5.93	36453	0.87%
4	-0.15671	-6.52	-0.13654	-4.64	0.10214	4.57	36743	0.95%
5	-0.24359	-9.41	-0.17971	-5.59	0.14668	5.98	36671	1.04%
6	-0.29692	-10.62	-0.20147	-5.74	0.16696	6.24	36576	1.08%
7	-0.30899	-10.49	-0.21400	-5.81	0.20361	7.17	36404	1.22%
8	-0.37530	-12.04	-0.23141	-5.85	0.19974	6.59	36230	1.29%
9	-0.42616	-12.76	-0.23148	-5.41	0.22316	6.82	35975	1.39%
10	-0.45994	-13.15	-0.29129	-6.36	0.25806	7.36	35613	1.56%
11	-0.52635	-13.93	-0.30686	-6.11	0.31132	8.12	34911	1.75%

Table 5. Differential impact of prior period normal and abnormal accruals on forecast errors, by forecast horizon

$$FE_{i,t} = \alpha + \sum_{k=89}^{99} Year_k + \sum_{l=1}^{14} Industry_l + \beta_1 NormalAccruals_{i,t-1} + \beta_2 AbnormalAccruals_{i,t-1} + e_{i,t}$$

Month	Intercept	t-stat	β_1	t-stat	β_2	t-stat	N	R-sq	$H_0: \beta_1 = \beta_2$	
									F-stat	p
1	-0.25615***	-6.04	-0.01775	-0.27	-0.06884*	-1.72	16399	1.05%	0.44	0.509
2	-0.15655***	-6.15	-0.02219	-0.45	-0.06129***	-2.26	35939	0.66%	0.48	0.4862
3	-0.12042***	-5.34	-0.08261	-1.63	-0.11234***	-4.01	36959	0.66%	0.26	0.6095
4	-0.14833***	-6.19	-0.05801	-1.04	-0.10878***	-3.60	37103	0.75%	0.63	0.4271
5	-0.22628***	-8.75	-0.10126	-1.64	-0.18048***	-5.47	36867	0.82%	1.27	0.2595
6	-0.28693***	-10.23	-0.10815	-1.61	-0.21258***	-5.81	36659	0.93%	1.85	0.1741
7	-0.29862***	-10.10	-0.04814	-0.68	-0.25921***	-6.73	36345	1.02%	6.83	0.009
8	-0.36708***	-11.72	-0.08522	-1.13	-0.29924***	-7.20	36087	1.15%	6.17	0.013
9	-0.40641***	-12.04	-0.04504	-0.54	-0.30058***	-6.65	35709	1.24%	7.43	0.0064
10	-0.43019***	-12.09	-0.05804	-0.64	-0.41648***	-8.61	35217	1.40%	12.4	0.0004
11	-0.50844***	-13.27	-0.21052***	-2.15	-0.39602***	-7.47	34404	1.50%	2.81	0.0939

$$FE_{i,t} = \alpha + \sum_{k=89}^{99} Year_k + \sum_{l=1}^{14} Industry_l + \beta_0 CashFlows + \beta_1 NormalAccruals_{i,t-1} + \beta_2 AbnormalAccruals_{i,t-1} + e_{i,t}$$

Month	Intercept	t-stat	β_1	t-stat	β_2	t-stat	β_0	t-stat	N	R-sq	$H_0: \beta_1 = \beta_2$	
											F-stat	p
1	-0.22934***	-5.06	0.03954	0.49	-0.05097	-1.12	0.11147***	3.91	15662	1.14%	0.99	0.32090
2	-0.14390***	-5.45	-0.04808	-0.85	-0.04969	-1.63	0.12059***	5.97	34340	0.80%	0.00	0.97980
3	-0.12303***	-5.32	-0.07415	-1.29	-0.09625***	-3.07	0.12609***	6.08	35498	0.79%	0.12	0.73200
4	-0.15009***	-6.13	-0.10770	-1.72	-0.14505***	-4.33	0.10174***	4.53	35782	0.84%	0.28	0.59550
5	-0.22093***	-8.36	-0.11157	-1.63	-0.19238***	-5.27	0.15020***	6.08	35714	0.98%	1.12	0.29030
6	-0.28126***	-9.81	-0.09828	-1.31	-0.22506***	-5.60	0.16912***	6.25	35640	1.08%	2.31	0.12860
7	-0.28530***	-9.49	-0.02042	-0.26	-0.25760***	-6.11	0.20502***	7.16	35447	1.21%	7.35	0.00670
8	-0.35794***	-11.25	-0.07515	-0.90	-0.27390***	-6.08	0.19558***	6.41	35289	1.30%	4.58	0.03230
9	-0.40402***	-11.84	-0.00972	-0.10	-0.28605***	-5.88	0.22074***	6.69	35032	1.41%	7.67	0.00560
10	-0.43156***	-12.03	-0.03986	-0.40	-0.36007***	-6.92	0.25382***	7.17	34678	1.56%	8.71	0.00320
11	-0.50624***	-13.07	-0.21459***	-2.02	-0.33043***	-5.80	0.30996***	8.00	33996	1.73%	0.97	0.32480

Table 6: Impact of analyst following on earnings forecast error and accrual inefficiency in consensus forecasts.

Panel A: Working Capital Accruals

$$FE_{i,t,j} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlow_{i,t-1} + \beta_2 Accruals_{i,t-1} + \beta_4 AnalystFollowing_{i,t,j} + \beta_3 Accruals_{i,t-1} \cdot AnalystFollowing_{i,t,j} + \beta_5 ForecastHorizon_{i,t,j} + \beta_5 Size_{i,t} + \beta_6 Accruals_{i,t-1} \cdot Size_{i,t} + e_{i,t,j}$$

Month	Intercept	Cash Flow	Accruals	Accruals x Following	Analyst Following	Size	Size x Accruals	Obs.	R-sq
1	-0.29988 (-0.98)	0.01825 (0.59)	-0.2569*** (-3.21)	0.03333*** (2.22)	0.01529*** (9.07)	-0.00393 (-1.51)	-0.0427 (-0.65)	7458	2.34%
2	-0.17512*** (-3.48)	0.02003 (0.93)	-0.2444*** (-4.16)	0.02966*** (2.80)	0.01615*** (13.31)	-0.00191 (-1.21)	-0.0508 (-1.09)	16314	2.17%
3	-0.13837*** (-3.79)	0.01427 (0.65)	-0.3128*** (-5.01)	0.03917*** (3.35)	0.01632*** (12.91)	-0.00214 (-1.32)	-0.1098*** (-2.36)	16863	1.95%
4	-0.18391*** (-4.96)	0.00389 (0.16)	-0.2989*** (-4.52)	0.03720*** (2.86)	0.01739*** (12.82)	-0.00110 (-0.62)	-0.1066** (-2.13)	16981	2.02%
5	-0.27344*** (-6.77)	0.01220 (0.46)	-0.3533*** (-4.85)	0.03515*** (2.38)	0.01922*** (12.94)	-0.00031 (-0.15)	-0.1112** (-2.01)	16932	2.15%
6	-0.39777*** (-8.99)	-0.00959 (-0.33)	-0.4435*** (-5.47)	0.04407*** (2.60)	0.02310*** (14.11)	-0.00008 (-0.03)	-0.1261** (-2.07)	16889	2.28%
7	-0.36216*** (-7.77)	0.00579 (0.18)	-0.5197*** (-6.22)	0.04622*** (2.61)	0.02354*** (13.71)	0.00029 (0.13)	-0.1656*** (-2.59)	16784	2.38%
8	-0.47332*** (-9.62)	0.01401 (0.42)	-0.5557*** (-6.26)	0.03852** (1.99)	0.02332*** (12.77)	0.00266 (1.07)	-0.1224 (-1.76)	16702	2.48%
9	-0.52625*** (-9.92)	0.02961 (0.83)	-0.5764*** (-5.926)	0.02733 (1.28)	0.02612*** (13.44)	0.00257 (0.98)	-0.1076 (-1.46)	16551	2.65%
10	-0.57019*** (-10.25)	0.04237 (1.09)	-0.6391*** (-6.18)	0.02038 (0.89)	0.02706*** (13.33)	0.00238 (0.86)	-0.1052 (-1.34)	16357	2.77%
11	-0.67622*** (-11.15)	0.06328 (1.47)	-0.5635*** (-5.05)	-0.00136 (-0.05)	0.02969*** (13.48)	0.00351 (1.14)	-0.0849 (-1.01)	16021	3.00%

Table 6 (cont.) Impact of analyst following on earnings forecast error and accrual inefficiency in consensus forecasts.

Panel B: Working Capital Accruals (Sloan)

$$FE_{i,t,j} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlow_{i,t-1} + \beta_2 Accruals_{i,t-1} + \beta_4 AnalystFollowing_{i,t,j} + \beta_3 Accruals_{i,t-1} \cdot AnalystFollowing_{i,t,j} + \beta_5 ForecastHorizon_{i,t,j} + \beta_5 Size_{i,t} + \beta_6 Accruals_{i,t-1} \cdot Size_{i,t} + e_{i,t,j}$$

Month	Intercept	Cash Flow	Accruals	Accruals x Following	Analyst Following	Size	Size x Accruals	Obs.	R-sq
1	-0.3916*** (-12.31)	0.0376 (1.55)	-0.0855 (-1.58)	0.0094 (1.21)	0.0141*** (13.58)	-0.0039*** (-2.86)	-0.0012 (-0.07)	15121	2.13%
2	-0.3070*** (-13.80)	0.0358** (2.09)	-0.1402*** (-3.58)	0.0142*** (2.27)	0.0142*** (17.93)	-0.0022** (-1.97)	-0.0048 (-0.36)	32804	1.79%
3	-0.2829*** (-13.17)	0.0339* (1.91)	-0.1751*** (-4.29)	0.0161*** (2.43)	0.0151*** (18.12)	-0.0024** (-2.14)	-0.0054 (-0.42)	33836	1.76%
4	-0.3029*** (-13.15)	0.0225 (1.15)	-0.2739*** (-6.21)	0.0237*** (3.23)	0.0165*** (18.01)	-0.0016 (-1.37)	0.0014 (0.10)	34066	1.88%
5	-0.3867*** (-15.45)	0.0460** (2.14)	-0.3357*** (-6.91)	0.0293*** (3.48)	0.0183*** (18.21)	-0.0005 (-0.41)	0.0012 (0.08)	34004	2.08%
6	-0.4607*** (-17.06)	0.0401 (1.70)	-0.3764*** (-7.15)	0.0319*** (3.47)	0.0209*** (19.26)	-0.0006 (-0.42)	-0.0002 (-0.01)	33907	2.32%
7	-0.4897*** (-17.14)	0.0616*** (2.46)	-0.4041*** (-7.30)	0.0344*** (3.49)	0.0216*** (18.81)	-0.0000 (-0.03)	0.0035 (0.20)	33711	2.37%
8	-0.5464*** (-18.13)	0.0686*** (2.56)	-0.3716*** (-6.24)	0.0225** (2.09)	0.0217*** (17.91)	0.0019 (1.17)	0.0142 (0.76)	33551	2.47%
9	-0.5962*** (-18.45)	0.0818*** (2.83)	-0.4291*** (-6.65)	0.0255** (2.18)	0.0238*** (18.34)	0.0018 (1.07)	0.0127 (0.63)	33260	2.67%
10	-0.6559*** (-19.36)	0.0971*** (3.10)	-0.4509*** (-6.61)	0.0233* (1.91)	0.0249*** (18.27)	0.0018 (1.03)	0.0271 (1.28)	32897	2.79%
11	-0.7361*** (-20.07)	0.1271*** (3.70)	-0.4408*** (-5.96)	0.0238* (1.78)	0.0267*** (18.13)	0.0021 (1.06)	0.0109 (0.47)	32221	2.99%

Table 6 (cont.): Impact of analyst following on earnings forecast error and accrual inefficiency in consensus forecasts.

Panel C: Total Accruals

$$FE_{i,t,j} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlow_{i,t-1} + \beta_2 Accruals_{i,t-1} + \beta_4 AnalystFollowing_{i,t,j} + \beta_3 Accruals_{i,t-1} \cdot AnalystFollowing_{i,t,j} + \beta_5 ForecastHorizon_{i,t,j} + \beta_5 Size_{i,t} + \beta_6 Accruals_{i,t-1} \cdot Size_{i,t} + e_{i,t,j}$$

Month	Intercept	Cash Flow	Accruals	Accruals x Analyst Following	Analyst Following	Size	Size x Accruals	Obs.	R-sq
1	-0.3406*** (-7.72)	0.0376 (1.45)	-0.0660 (-1.36)	0.0052 (0.73)	0.0136*** (13.24)	-0.0071 (-1.43)	0.0083 (0.94)	15976	2.34%
2	-0.2641*** (-9.89)	0.0472*** (2.53)	-0.0990*** (-2.88)	0.0095 (1.76)	0.0144*** (18.52)	-0.0029 (-0.83)	0.0066 (1.02)	35143	2.17%
3	-0.2353*** (-10.14)	0.0472*** (2.52)	-0.1449*** (-4.19)	0.0117** (2.11)	0.0151*** (18.88)	-0.0040 (-1.14)	0.0048 (0.73)	36304	1.95%
4	-0.2714*** (-11.03)	0.0326 (1.61)	-0.1926*** (-5.28)	0.0159*** (2.57)	0.0166*** (18.86)	-0.0035 (-0.90)	0.0054 (0.76)	36580	2.02%
5	-0.3699*** (-13.94)	0.0584*** (2.63)	-0.2329*** (-5.78)	0.0165*** (2.34)	0.0183*** (19.07)	-0.0040 (-0.95)	0.0010 (0.13)	36503	2.15%
6	-0.4351*** (-15.18)	0.0709*** (2.91)	-0.2563*** (-5.79)	0.0179*** (2.33)	0.0205*** (19.69)	-0.0049 (-1.08)	0.0004 (0.05)	36391	2.28%
7	-0.4546*** (-15.05)	0.0961*** (3.72)	-0.2731*** (-5.91)	0.0201*** (2.43)	0.0213*** (19.40)	-0.0036 (-0.75)	-0.0001 (-0.01)	36215	2.38%
8	-0.5303*** (-16.58)	0.0850*** (3.09)	-0.2540*** (-5.14)	0.0125 (1.39)	0.0222*** (19.05)	-0.012 (-0.23)	-0.0012 (-0.12)	36043	2.48%
9	-0.5958*** (-17.38)	0.1042*** (3.45)	-0.2346*** (-4.31)	0.0080 (0.82)	0.0239*** (19.15)	0.0000 (0.00)	-0.0002 (-0.02)	35784	2.65%
10	-0.6328*** (-17.63)	0.1207*** (3.66)	-0.3030*** (-5.23)	0.0114 (1.11)	0.0249*** (19.11)	0.0001 (0.02)	0.0057 (0.53)	35412	2.77%
11	-0.7121*** (-18.36)	0.1575*** (4.40)	-0.3002*** (-4.74)	0.0102 (0.91)	0.0265*** (18.95)	0.00024 (0.41)	-0.00177 (-0.15)	34716	3.00%

Table 7: Impact of analyst following on earnings forecast error and accrual inefficiency in consensus forecasts.

$$\begin{aligned}
 FE_{i,t,j} = & \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlow_{i,t-1} + \beta_2 Accruals_{i,t-1} + \\
 & + \beta_4 AnalystFollowing_{i,t,j} + \beta_3 Accruals_{i,t-1} \cdot AnalystFollowing_{i,t,j} + \\
 & + \beta_5 ForecastHorizon_{i,t,j} + \beta_6 Size_{i,t} + \beta_6 Accruals_{i,t-1} \cdot Size_{i,t} + e_{i,t,j}
 \end{aligned}$$

Panel A: Working Capital Accruals

	Predicted Sign	Actual Values	Decile Portfolios
Intercept		0.19945*** (11.91)	0.32889*** (18.44)
Cash Flows _{t-1}		0.01403 (0.92)	N/A
Accruals _{t-1}	-	-0.9390*** (-20.83)	-0.36742*** (-22.83)
Analyst Following		0.01829*** (32.71)	0.011587*** (10.17)
Analyst Following*Accruals _{t-1}	+	0.03759*** (4.51)	.001784*** (7.83)
Forecast Horizon		-0.09664*** (-99.12)	-0.09599*** (-101.73)
Size		0.0051 (1.07)	0.000046 (1.02)
Size* Accruals _{t-1}		-0.00097 (-0.89)	-0.00143 (-1.32)
R-sq		6.8%	6.6%
N		189,112	204,552

(***), (**), and (*) denote significance at 1%, 5%, and 10% respectively.
See Appendix for definitions of variables.

Table 7 (cont.): Impact of analyst following on earnings forecast error and accrual inefficiency in consensus forecasts.

$$\begin{aligned}
 FE_{i,j,t} = & \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlow_{i,t-1} + \beta_2 Accruals_{i,t-1} + \\
 & + \beta_4 AnalystFollowing_{i,j,t} + \beta_3 Accruals_{i,t-1} \cdot AnalystFollowing_{i,j,t} + \\
 & + \beta_5 ForecastHorizon_{i,j,t} + \beta_5 Size_{i,t} + \beta_6 Accruals_{i,t-1} \cdot Size_{i,t} + e_{i,j,t}
 \end{aligned}$$

Panel B: Working capital accruals (Sloan)

	Predicted Sign	Actual Values	Decile Portfolios
<i>Intercept</i>		0.02682*** (2.61)	0.17141*** (14.66)
<i>Cash Flows_{t-1}</i>		0.07883*** (6.61)	
<i>Accruals_{t-1}</i>	-	-0.62123*** (-22.04)	-0.02654*** (-22.59)
<i>Analyst Following</i>		0.01651*** (42.15)	0.00838*** (11.55)
<i>Analyst Following*Accruals_{t-1}</i>	+	0.039156*** (8.75)	0.0016*** (10.94)
<i>Forecast Horizon</i>		-0.09469*** (-138.06)	-0.09463*** (-137.98)
<i>Size</i>		0.01031*** (2.53)	0.0000085*** (2.08)
<i>Size* Accruals_{t-1}</i>		-0.00065 (-1.24)	0.00011*** (-2.09)
<i>R-sq</i>		6.2%	6.1%
<i>N</i>		378,705	378,830

(***), (**) and (*) denote significance at 1%, 5%, and 10% respectively.
See Appendix for definitions of variables.

Table 7 (cont.): Impact of analyst following on earnings forecast error and accrual inefficiency in consensus forecasts.

$$\begin{aligned}
 FE_{i,t,j} = & \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlow_{i,t-1} + \beta_2 Accruals_{i,t-1} + \\
 & + \beta_4 AnalystFollowing_{i,t,j} + \beta_3 Accruals_{i,t-1} \cdot AnalystFollowing_{i,t,j} + \\
 & + \beta_5 ForecastHorizon_{i,t,j} + \beta_5 Size_{i,t} + \beta_6 Accruals_{i,t-1} \cdot Size_{i,t} + e_{i,t,j}
 \end{aligned}$$

Panel C: Total Accruals

	Predicted Sign	Actual Values	Decile Portfolios
<i>Intercept</i>		0.06786*** (6.25)	0.2138*** (17.95)
<i>Cash Flows_{t-1}</i>		0.10849*** (8.35)	N/A
<i>Accruals_{t-1}</i>	-	-0.4147*** (-18.44)	-0.027*** (-23.95)
<i>Analyst Following</i>		0.01652*** (42.36)	0.0086*** (12.15)
<i>Analyst Following*Accruals_{t-1}</i>	+	0.01996*** (5.15)	0.00162*** (11.41)
<i>Forecast Horizon</i>		-0.0933*** (-142.14)	-0.0932*** (142.07)
<i>Size</i>		0.00603* (1.75)	0.000023 (0.67)
<i>Size* Accruals_{t-1}</i>		-0.00072* (-1.70)	-0.00015*** (-3.60)
<i>R-sq</i>		6.3%	6.2%
<i>N</i>		407,402	407,420

(***), (**), and (*) denote significance at 1%, 5%, and 10% respectively.
See Appendix for definitions of variables.

Table 8. Impact of analyst forecasting ability on the extent of accrual inefficiency in their forecasts

$$FE_{i,j} = \alpha + \sum_{k=1999}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlows_{i,j-1} + \beta_{2H} HAbility \cdot Accruals_{i,j-1} + \beta_{2M} MAbility \cdot Accruals_{i,j-1} + \beta_{2L} LAbility \cdot Accruals_{i,j-1} + \beta_3 Ability + \beta_4 MeanHorizon + \beta_5 AnalystFollowing_{i,j} + \beta_6 Size_{i,j} + e_{i,j}$$

Panel A: Working Capital Accruals

	Ability:	Actual Values	Portfolio Assignments
<i>Intercept</i>		-0.48933 ^{***} (-4.57)	-0.02941 (-0.22)
<i>Cash Flows</i>		-0.02137 (-0.37)	N/A
<i>Accruals</i>	<i>High</i>	-0.43547 [*] (-1.85)	-0.01753 (-1.21)
	<i>Medium</i>	-0.50876 ^{***} (-3.14)	-0.04554 ^{***} (-5.37)
	<i>Low</i>	-2.60339 ^{***} (-5.42)	-0.14099 ^{***} (-6.88)
<i>Ability</i>		0.11773 ^{***} (3.31)	-0.10488 (-1.39)
<i>Horizon</i>		-0.08007 ^{***} (-9.75)	-0.07899 ^{***} (-9.68)
<i>Analyst Following</i>		0.01457 ^{***} (6.56)	0.01461 ^{***} (6.67)
<i>Size</i>		0.002 (-0.30)	0.001 (-0.42)
<i>N</i>		70,701	71,099
<i>R-sq</i>		5.5%	5.8%

Tests of Hypotheses

	F-stat	F-stat
$\beta_{2H} > \beta_{2M} > \beta_{2L}$	9.17 ^{***}	14.1 ^{***}
$\beta_{2H} > \beta_{2L}$	16.34 ^{***}	18.17 ^{***}
$\beta_{2H} > \beta_{2M}$	0.05	3.62 ^{**}
$\beta_{2M} > \beta_{2L}$	17.59 ^{***}	27.15 ^{***}

(***), (**), and (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

Please refer to the Appendix for definitions of the variables

Table 8. Impact of analyst forecasting ability on the extent of accrual inefficiency in their forecasts

$$FE_{i,t,j} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlows_{i,t-1} + \\ + \beta_{2H} HAbility \cdot Accruals_{i,t-1} + \beta_{2M} MAbility \cdot Accruals_{i,t-1} + \beta_{2L} LAbility \cdot Accruals_{i,t-1} + \\ + \beta_3 Ability + \beta_4 MeanHorizon + \beta_5 AnalystFollowing_{i,t,j} + \beta_6 Size_{i,t} + e_{i,t,j}$$

Panel B: Working Capital Accruals – Sloan [1996]

	Ability:	Actual Values	Portfolio Assignments
<i>Intercept</i>		-0.33400 ^{***} (-4.44)	-0.14003 (-1.41)
<i>Cash Flows</i>		0.04924 (0.81)	N/A
<i>Accruals</i>	<i>High</i>	0.04112 (0.21)	0.01627 (1.45)
	<i>Medium</i>	-0.15097 (-1.19)	-0.00063 (-0.10)
	<i>Low</i>	-0.98412 ^{***} (-2.79)	-0.05342 ^{***} (-3.55)
<i>Ability</i>		0.11492 ^{***} (4.35)	-0.04074 ^{***} (-0.73)
<i>Horizon</i>		-0.07545 ^{***} (-12.17)	-0.07526 ^{***} (-12.14)
<i>Analyst Following</i>		0.01163 ^{***} (6.78)	0.01216 ^{***} (7.17)
<i>Size</i>		0.001 ^{***} (2.81)	0.001 ^{***} (2.73)
<i>N</i>		148,402	148,424
<i>R-sq</i>		3.6%	3.6%

Tests of Hypotheses

	F-stat	F-stat
$\beta_{2H} > \beta_{2M} > \beta_{2L}$	3.11 ^{**}	7.95 ^{***}
$\beta_{2H} > \beta_{2L}$	6.20 ^{***}	10.44 ^{***}
$\beta_{2H} > \beta_{2M}$	0.82	2.25
$\beta_{2M} > \beta_{2L}$	4.65 ^{**}	15.47 ^{***}

(***), (**), and (*) denote statistical significance at 1%, 5%, and 10% levels respectively.

Please refer to the Appendix for definitions of the variables

Table 8. Impact of analyst forecasting ability on the extent of accrual inefficiency in their forecasts

$$FE_{i,j} = \alpha + \sum_{k=89}^{99} \gamma_k Year_k + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlows_{i,j-1} + \\ + \beta_{2H} HAbility \cdot Accruals_{i,j-1} + \beta_{2M} MAbility \cdot Accruals_{i,j-1} + \beta_{2L} LAbility \cdot Accruals_{i,j-1} + \\ + \beta_3 Ability + \beta_4 MeanHorizon + \beta_5 AnalystFollowing_{i,j} + \beta_6 Size_{i,j} + e_{i,j}$$

Panel C: Total Accruals			
	Ability:	Actual Values	Portfolio Assignments
<i>Intercept</i>		-0.21394 *** (-2.85)	-0.03178 (-0.33)
<i>Cash Flows</i>		0.03026 (0.50)	N/A
<i>Accruals</i>	<i>High</i>	-0.06782 (-0.42)	-0.00399 (-0.38)
	<i>Medium</i>	-0.33901 *** (-3.17)	-0.01193 ** (-1.95)
	<i>Low</i>	-0.84871 *** (-2.88)	-0.04031 *** (-2.87)
<i>Ability</i>		0.09645 *** (3.85)	0.00747 (0.14) ***
<i>Horizon</i>		-0.07315 *** (-12.76)	-0.07312 (-12.76)
<i>Analyst Following</i>		0.01464 *** (9.81)	0.01479 *** (10.00)
<i>Size</i>		0.0002 (-0.37)	0.0002 (-0.41)
<i>N</i>		153,205	153,205
<i>R-sq</i>		3.7%	3.7%
Tests of Hypotheses			
	F-stat	F-stat	F-stat
$\beta_{2H} > \beta_{2M} > \beta_{2L}$	2.68 *		2.68 *
$\beta_{2H} > \beta_{2L}$	4.99 **		3.25 *
$\beta_{2H} > \beta_{2M}$	2.32 *		0.57
$\beta_{2M} > \beta_{2L}$	2.32 *		5.12 **

(***), (**), and (*) denote statistical significance at 1%, 5%, and 10% levels respectively. Please refer to the Appendix for definitions of the variables

Table 9. Impact of analyst forecasting ability on the extent of accrual inefficiency in their Forecasts: the case of normal vs. abnormal accruals.

$$\begin{aligned}
 MFE_{i,j} = & \alpha + \sum_{i=1999}^{2002} \gamma_i Year_i + \sum_{j=1}^{14} \delta_j Industry_j + \beta_1 CashFlows_{i,j-1} + \\
 & + \beta_{2H} HAbility_i \cdot NAccruals_{i,j-1} + \beta_{2M} MAbility_i \cdot NAccruals_{i,j-1} + \beta_{2L} LAbility_i \cdot NAccruals_{i,j-1} + \\
 & + \beta_{3H} HAbility_i \cdot AbAccruals_{i,j-1} + \beta_{3M} MAbility_i \cdot AbAccruals_{i,j-1} + \beta_{3L} LAbility_i \cdot AbAccruals_{i,j-1} + \\
 & + \beta_4 Ability + \beta_5 MeanHorizon + \beta_6 AnalystFollowing_{i,j,j} + \beta_7 Size_{i,j} + e_{i,j,j}
 \end{aligned}$$

	Ability:	Parameters:	
<i>Intercept</i>		-0.2089*** (-2.69)	
<i>Cash Flows</i>		0.02340 (0.69)	
		Normal	Abnormal
	<i>High</i>	0.5350 (1.73)	-0.3218 (-1.61)
<i>Accruals</i>	<i>Medium</i>	-0.2672 (-1.34)	-0.3390*** (-2.66)
	<i>Low</i>	-0.9362* (-1.76)	-0.7651*** (-2.15)
<i>Ability</i>		0.1110*** (4.09)	
<i>Horizon</i>		-0.0732*** (-12.53)	
<i>Analyst Following</i>		0.0147*** (9.75)	
<i>Size</i>		0.0001 (-0.24)	
<i>N</i>		149,990	
<i>R-sq</i>		3.8%	

Tests of Hypotheses

	Normal Accruals		Abnormal Accruals	
	F-stat		F-stat	
$\beta_{2H} > \beta_{2M} > \beta_{2L}$	3.64**		$\beta_{3H} > \beta_{3M} > \beta_{3L}$	0.63
$\beta_{2H} > \beta_{2L}$	5.23**		$\beta_{3H} > \beta_{3L}$	1.11
$\beta_{2H} > \beta_{2M}$	5.69**		$\beta_{3H} > \beta_{3M}$	0.01
$\beta_{2M} > \beta_{2L}$	1.16		$\beta_{3M} > \beta_{3L}$	1.18

(***), (**), and (*) denote statistical significance at 1%, 5%, and 10% levels respectively. Please refer to the Appendix for definitions of the variables

APPENDIX C - FIGURES

LIST OF FIGURES

Figure 1 Analysts' Accrual Inefficiency Across Forecast Horizons and Types of Accruals (Deciles).....	84
Figure 2 Analysts' Accrual Inefficiency Across Forecast Horizons and Types of Accruals (Actual Values).....	85
Figure 3 Analysts' Accrual Inefficiency Across Forecast Horizons and Types of Accruals, controlled for Cash Flows.....	86
Figure 4: Differential impact of Normal and Abnormal Accruals on Analyst Accrual Inefficiency	87
Figure 5: Differential impact of Normal and Abnormal Accruals on Analyst Accrual Inefficiency, controlled for Cash Flows	88

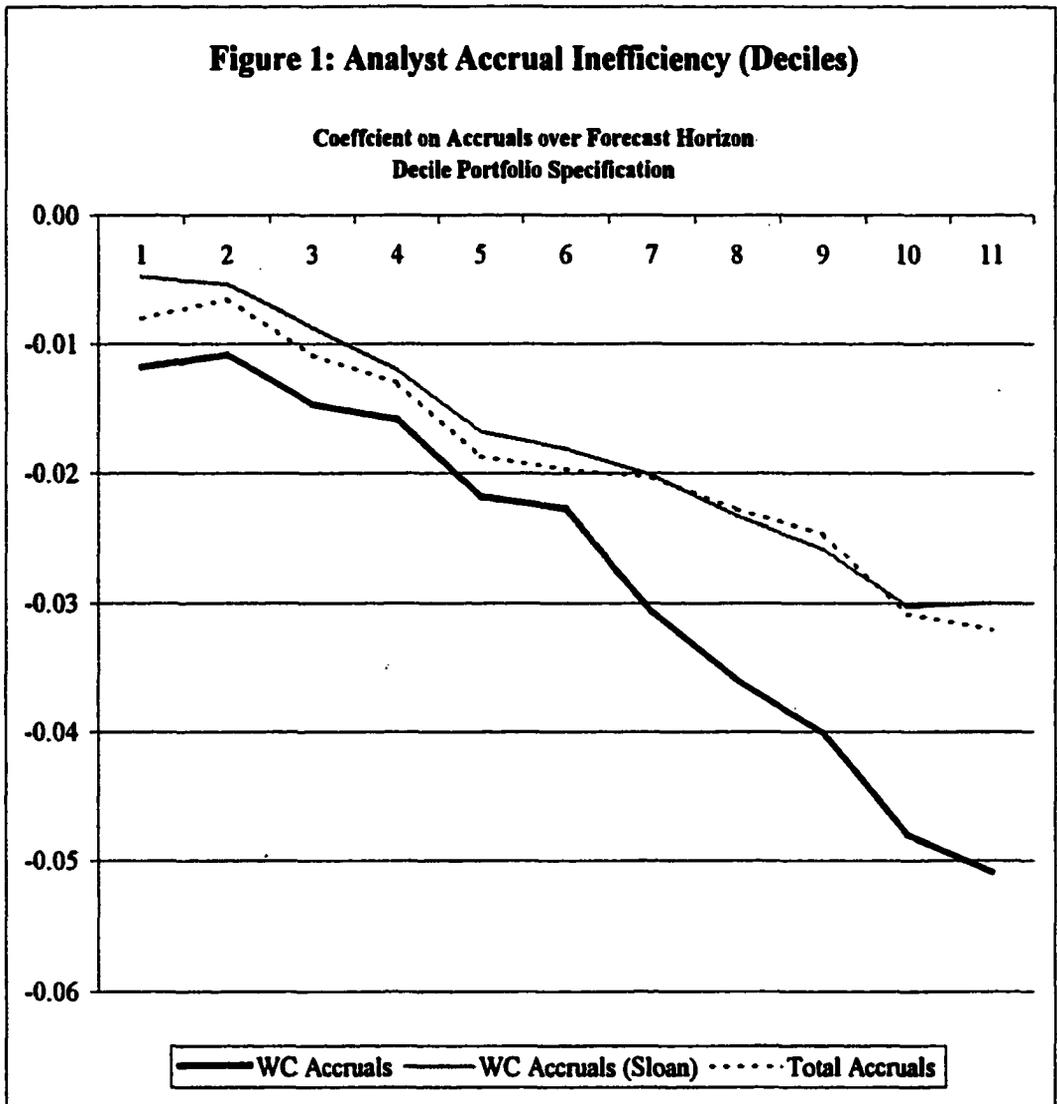
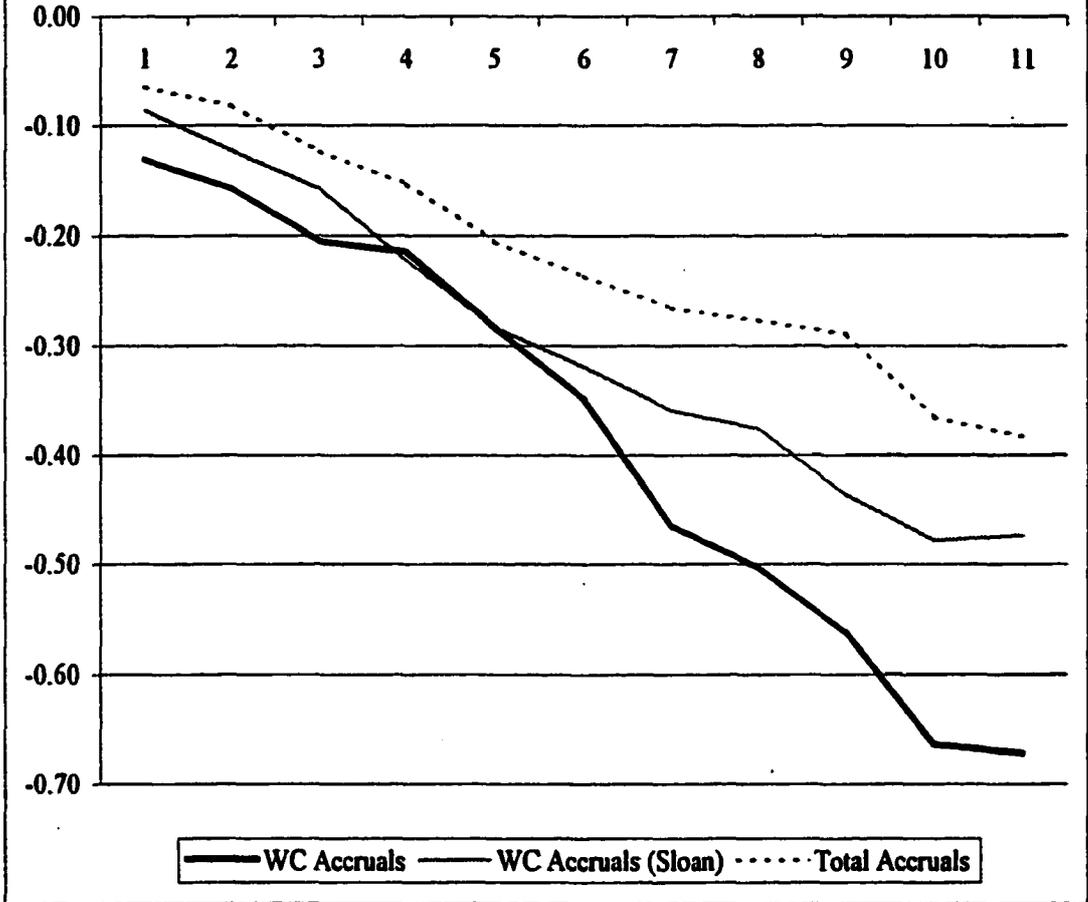


Figure 2: Analyst Accrual Inefficiency (Actual Values)
Coefficient on Accruals over Forecast Horizon
Actual Values



**Figure 3: Analyst Accrual Inefficiency
(Actual Values controlled for Cash Flows)**

Coefficient on Accruals over Forecast Horizon
Actual Values, controlled for Cash Flows

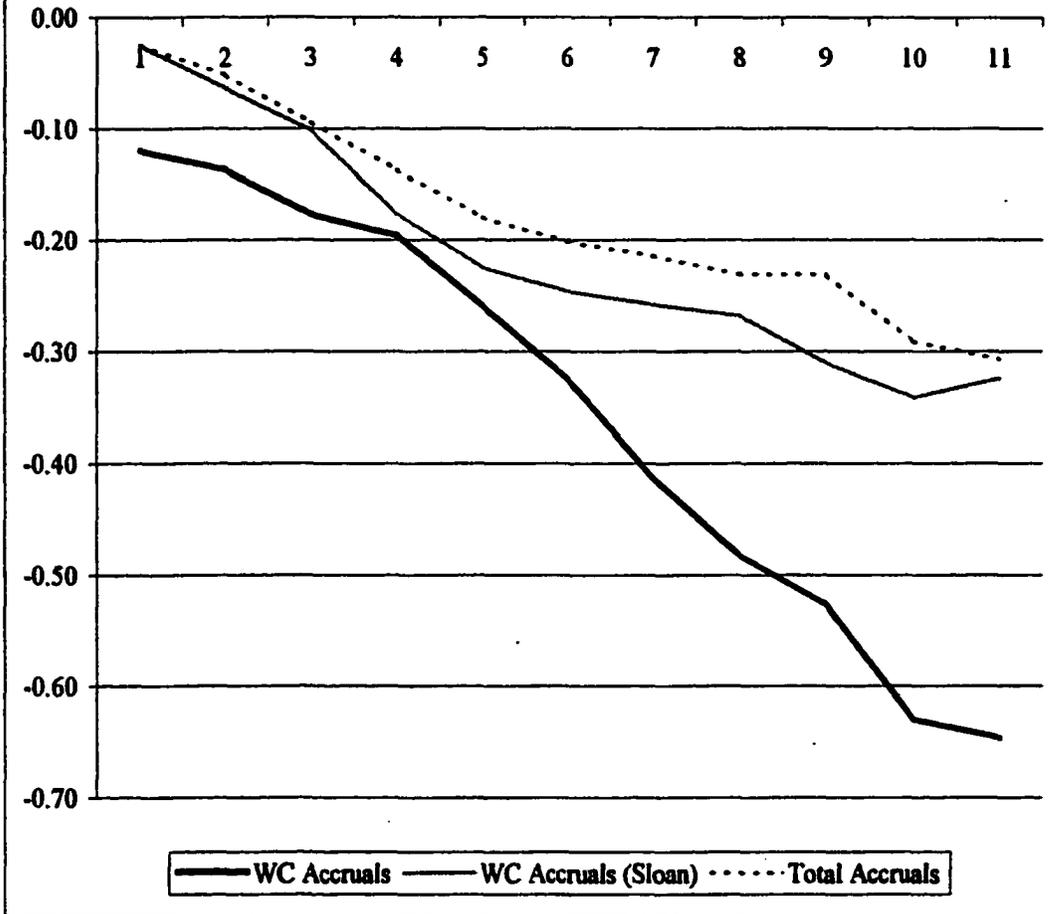


Figure 4: Differential impact of Normal and Abnormal Accruals on Analysts' Accrual Inefficiency
Coefficients on Normal and Abnormal Accruals over Forecast Horizon

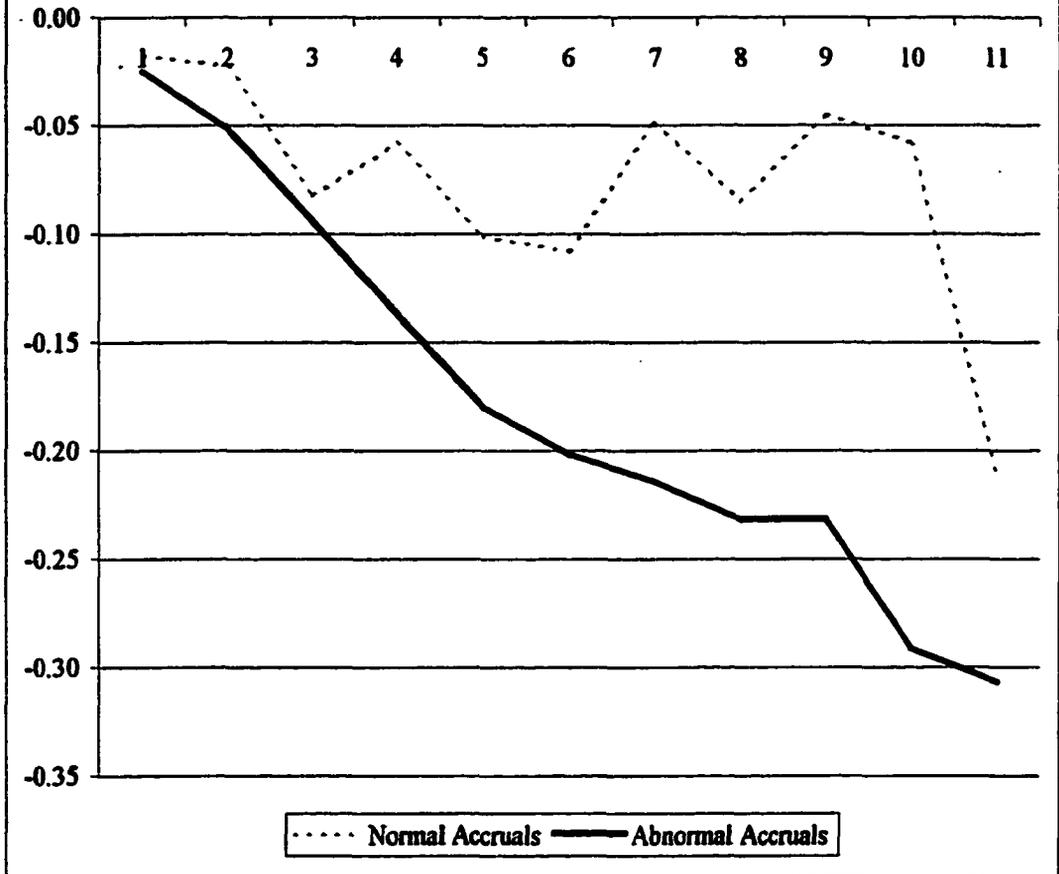
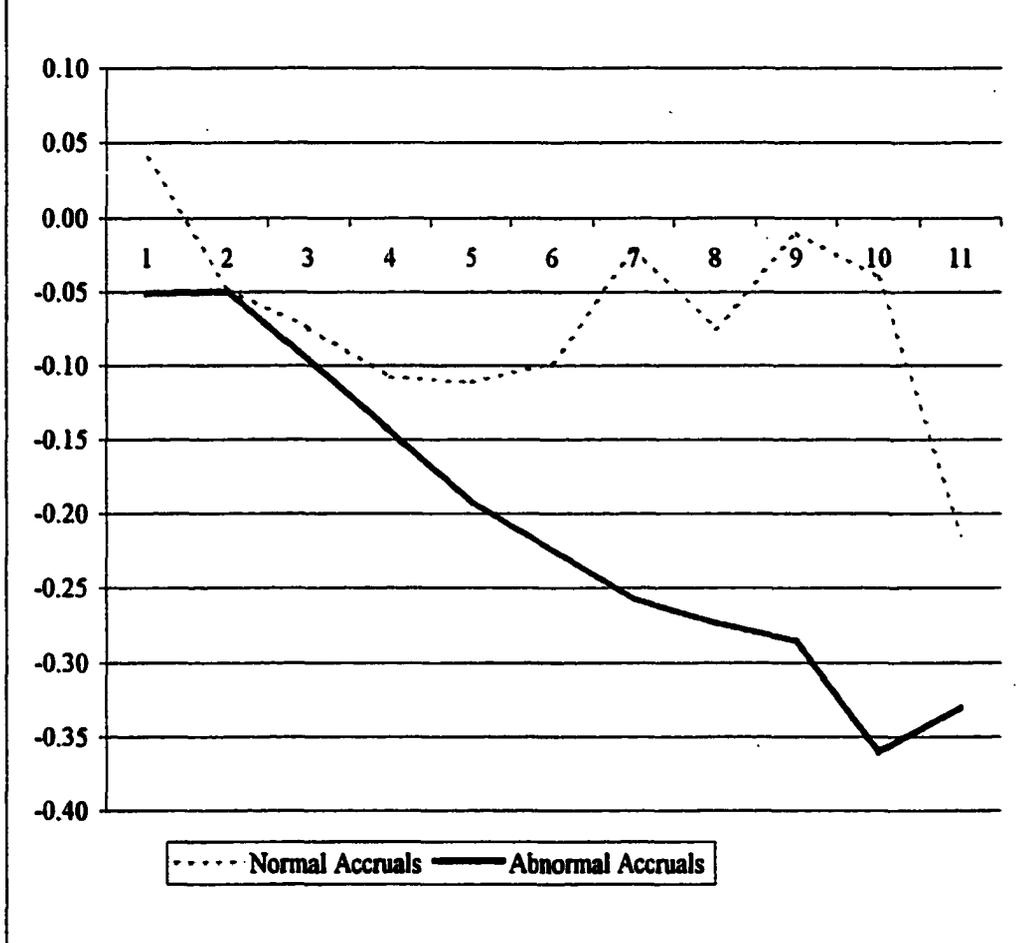


Figure 5: Differential impact of Normal and Abnormal Accruals on Analysts' Accrual Inefficiency
Coefficients on Normal and Abnormal Accruals over Forecast Horizon, controlled for Cash Flows



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