THE IMPACT OF EARNINGS MANAGEMENT AND EXPECTATIONS MANAGEMENT ON THE USEFULNESS OF EARNINGS AND ANALYST FORECASTS IN FIRM VALUATION

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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ABSTRACT

In this dissertation, I examine the impact of earnings management and expectations management on the usefulness of earnings and analyst forecasts in firm valuation. Earnings and analyst forecasts are important inputs into accounting valuation models. Their ability to reflect current and predict future firm performance can help valuation models predict intrinsic value. However, increasing earnings management and expectations management activities in recent years may have adversely affected the usefulness of these information items in firm valuation. This study shows that intrinsic value metrics estimated using manipulated earnings or forecasts have less ability to track stock prices and predict future returns through V/P ratios, providing evidence for the joint hypothesis of (i) long-term market efficiency and (ii) the negative impact of earnings management and expectations management on the usefulness of earnings and analyst forecasts in firm valuation. It contributes to the accounting literature in several ways. First, it challenges the conventional view that more accurate and less biased forecasts are necessarily of better quality and proposes to assess the quality of analyst forecasts directly by examining their usefulness. It also introduces an improved measure for expectations management and presents new evidence on (i) the usefulness of earnings and analyst forecasts in firm valuation; (ii) the negative impacts of earnings management and expectations management on this usefulness; and (iii) the overall performance of accounting valuation models in firm valuation.

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DEDICATION

I dedicate this thesis to my late father Decheng Tian (田德成), my mother Guizhi Bai (白桂芝) and my twin sister Lu Tian (田璐).

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CHAPTER 1: INTRODUCTION

1.1 Motivation

In this dissertation, I investigate the impact of earnings management and expectations management on the usefulness of earnings and analyst forecasts in firm valuation. This inquiry is motivated by several important prior studies. Notably, Skinner and Sloan (2002) demonstrate that stock market investors severely punish firms that fail to meet earnings expectations; while Bowen *et al.* (1995) and Burgstahler and Dichev (1997) find that firms that meet earnings benchmarks enhance their reputations with stakeholders such as customers, suppliers, and creditors, and hence enjoy better terms of trade. In addition, Healy (1985) argues that managers exercise accounting discretion to maximize the present value of their bonus compensation. In a related study, Matsunaga and Park (2001) find that failure to meet analyst forecasts results in pay cuts for CEOs. Taken together, the results from prior research suggest that factors such as stock market pressure, reputation effect, and private benefits for management all motivate firms to manipulate earnings and analyst earnings expectations to meet or beat expectations (MBE). Consistent with this view, recent studies such as Bartov *et al*. (2002) provide empirical evidence that firms manage both earnings and analyst expectations in order to report earnings that meet or exceed analyst expectations. In addition, Matsumoto (2002) provides evidence suggesting that firms have recently increased manipulation of both earnings and analyst earnings expectations.

To the best of my knowledge, a great deal of empirical research has been conducted to demonstrate the existence and assess the extent of earnings and expectations management, but little has been done to date to focus investigation on the implications and consequences of such manipulation. In reaction to increasing management manipulation and accounting scandals, the SEC has expressed the concern that the pressure to meet earnings expectations is eroding the quality of financial reporting. In response to this concern, I examine the impact of expectations management and earnings management on the usefulness of analyst forecasts and earnings in firm valuation.

1.2 Expectations Management and the Usefulness of Forecasts in Firm Valuation

Research in analyst forecasts, such as Fried and Givoly (1982) and Brown (1997), assesses forecast quality in terms of relative accuracy and bias. In the same vein, Ciccone (2003) reports that forecast dispersion and error have decreased consistently from 1990 to 2001. He attributes this trend to analysts' improved forecast abilities. However, this conclusion is subject to an important qualification: if the apparent improvement in analyst forecasts (in terms of higher accuracy and reduced bias) is an artefact of management's intentional expectations management activities for the purpose of meeting or beating expectations (MBE), then these manipulated forecasts will less accurately represent market expectations and will fail to predict future true economic performance. Thus, while the forecasts may appear more accurate and less biased, they may actually be of lower quality. As stressed by O'Brien (1988), although the properties of analyst forecasts, such as accuracy and bias, convey some information about forecast quality, the ultimate assessment of forecast quality should depend on the context within which the forecasts are being used.

In accounting research, analyst forecasts are used as critical inputs to accounting valuation models. Prior studies such as Dechow *et al.* (1999) and Frankel and Lee (1998) find that using analyst forecasts rather than forecasts based on past earnings improves the ability of these models to predict firm value. However, in the presence of ever-increasing expectations management activities, it is important to determine whether analyst forecasts are still useful in firm valuation. To assess this, I compare the abilities of valuation models estimated using manipulated and non-manipulated forecasts to predict firm value in Chapter 2

I first build on prior studies to develop an improved measure of expectations management. I then follow prior studies, in particular Lee *et al.*, (1999) and Dechow *et al.* (1999), to examine how well valuation models predict firm value by examining the ability of the intrinsic value metrics to track stock prices and predict future returns through the intrinsic value-to-price (V/P) ratios. If expectations management impairs the usefulness of analyst forecasts in firm valuation and reduces the ability of intrinsic value metrics to predict firm value then, under the market efficiency paradigm, I should observe that intrinsic value metrics estimated using manipulated forecasts have less ability to track stock price and predict future returns than intrinsic value metrics estimated using non-manipulated forecasts.

My empirical findings suggest that intrinsic value metrics estimated using manipulated forecasts (i) experience a greater decline in correlations with stock price from the beginning to the end of the year, (ii) yield V/P ratios with larger standard deviations and auto-correlations, and (iii) have less ability to identify mispriced stocks and predict future returns through V/P ratios. These results provide consistent evidence for the joint hypotheses that (1) expectations management impairs the usefulness of analyst forecasts in accounting valuation models and reduces the ability of intrinsic value metrics to predict firm value, and (2) the market is long-term efficient – it identifies and appropriately discounts for such manipulation over the course of a few months; consequently, in light of expectations management, stock price represents a more accurate measure of firm value..

1.3. Earnings Management and the Usefulness of Earnings in Firm Valuation

Earnings are often used in firm valuation by both the stock market and accounting valuation models. In particular, earnings are useful because they can capture truthful information relevant in assessing and predicting firm performance (Cheng, 2005). However, firms' deliberate earnings management activities may introduce errors into earnings and thereby reduce their ability to convey truthful information (Bernard, 1995). Whether or not the stock market or accounting valuation models can accurately predict firm values in the presence of earnings management is an empirical question. In Chapter 3, I investigate this issue to provide empirical evidence on the impact of earnings management on the usefulness of earnings in firm valuation.

As a first step of the inquiry I combine the aggregate accrual approach and the distribution of earnings after management approach to develop a more specific measure for earnings management. I then use the Ohlson (1995) residual income valuation model as the valuation framework to estimate the intrinsic value metric.

In the empirical analysis, I first compare the intrinsic value estimates (V) and the stock prices (P) for manipulators and non-manipulators to assess whether the market recognizes earnings management and discounts the stock prices for the firms that manipulate earnings. My empirical results show that, in the year prior to the earnings manipulation, stock prices and V/P ratios are similar for earnings manipulators and non-manipulators. However, in the year of manipulation, stock prices become significantly lower and V/P ratios become significantly higher for the manipulators than for the non-manipulators. These results suggest that the stock market does recognize and discount for earnings manipulation.

To further investigate whether the price discount is appropriate and whether intrinsic value metrics are good measures of firm value in the presence of earnings management, I examine and compare the performances of the V/P ratio portfolio strategies for the manipulators and non-manipulators to predict future returns. This strategy is motivated by the following argument. Under "long-term" market efficiency (*i.e.*, stocks can be mispriced in the short-run, but price is expected to converge to the true intrinsic value in the course of a few months), good intrinsic value metrics can identify stock mispricing and predict future returns through a V/P ratio portfolio strategy of buying underpriced stocks (firms with high V/P ratios) and selling overpriced stocks (firms with low V/P ratios). If earnings management impairs the usefulness of earnings and reduces the ability of accounting valuation models to predict firm value, then intrinsic value metrics estimated using manipulated earnings will have less ability to identify stock mispricing and predict future returns through V/P ratios. My empirical findings suggest that the V/P ratio strategy for the non-manipulator group earns significant positive returns, providing evidence consistent with long-term market efficiency and the ability of intrinsic value metrics to identify short-term mispricing and predict future returns through V/P ratios. In contrast, the V/P ratio portfolio strategy for the manipulator group is not able to predict future returns, providing evidence that earnings management introduces errors in earnings and reduces the ability of accounting valuation models to predict firm value.

1.4 Contributions and Implications

Earnings management and expectations management are two alternative mechanisms firms use to MBE. Consistent with recent studies (*e.g.*, Brown and Pinello, 2007), results from my dissertation suggest that firms are more likely to manipulate analyst expectations than to manipulate earnings in order to MBE (27% of the sample are classified as expectations manipulators, while only 16% are classified as earnings manipulators). This seems to suggest that it is more costly to manipulate earnings than to manipulate analyst expectations, because earnings are subject to the constraints of GAAP and the auditing process, while analyst expectations are not.

In addition, results from both the expectations management and earnings management chapters have important implications for the extent of market efficiency. In particular, my results indicate that in the absence of management manipulation, the market is long-term efficient and intrinsic value metrics represent good measures for firm value; consequently, intrinsic value metrics can identify short-term market mispricing and predict future returns through V/P ratios in the long-run when the market corrects its mispricing. However, management manipulation (both expectations management and earnings management) introduces errors into analyst forecasts and earnings and reduces the ability of accounting valuation models to predict firm value, but the stock market is efficient with such manipulation. Consequently we observe that, when manipulation occurs, intrinsic value estimates diverge from stock prices and are less able to identify stock mispricing and predict future returns through V/P ratios. Therefore, in light of management manipulation (*i.e.*, earnings management and expectations management), stock price represents a better measure for firm value than the intrinsic value metrics estimated from accounting valuation models.

This study contributes to accounting research in several respects. It contributes to the earnings management and expectations management literature by developing a more precise measure for expectations management and presenting new evidence on the impact of earnings and expectations manipulation on the usefulness of earnings and analyst forecasts in firm valuation. In addition, it contributes to the valuation literature by emphasizing an important determinant of the performance of accounting valuation models, namely management manipulation. In particular, it calls attention to the potential negative impact of expectations management and earnings management on the ability of accounting valuation models to predict firm intrinsic value.

CHAPTER 2: THE IMPACT OF EXPECTATIONS MANAGEMENT ON THE USEFULNESS OF ANALYST FORECASTS IN FIRM VAUATION

2.1 Introduction

In this chapter, I examine the impacts of expectations management on the usefulness of analyst forecasts in firm valuation. In accounting research, analyst forecasts are used as important inputs in firm valuation. Notably, Dechow *et al.* (1999) and Lee *et al.* (1999) show that using analyst forecasts, instead of forecasts based on past earnings, as a proxy for future earnings expectations improves the abilities of residual income valuation models to predict firms' intrinsic values. However, Vickers reports in *BusinessWeek* that, "Companies increasingly are talking down their profit prospects to Wall Street analysts, thereby lowering expectations." In this regard, Cotter *et al.* (2006) provide empirical evidence that analysts are influenced by management manipulation and quickly revise their earnings forecasts in direct response to management guidance. In addition, Richardson *et al.* (1999) document that firms walk down analyst forecasts from the beginning to the end of the year to create positive earnings surprises. In the light of such expectations management activities, an important research question is whether analyst forecasts are still useful in firm valuation? This chapter presents an investigation into this issue. Specifically, I first review related literature in Section 2.2. I then develop an "improved" measure for expectations management and introduce the valuation model used to estimate intrinsic value in Section 2.3. I present the empirical analyses and sensitivity analyses in Section 2.4 and 2.5. Lastly, I conclude this investigation with some remarks in Section 2.6.

2.2 Literature Review and Hypothesis Development

Financial analysts provide two broad types of services to stock market participants: (i) assimilating and processing publicly available information, and (ii) acquiring and disseminating new information (see Das 1998). Since the publication of seminal papers by Brown *et al.* (1987) and O'Brien (1988) that document the superiority of analyst forecasts to forecasts based on time-series models, analyst forecasts have come to be viewed as the best proxy for market expectations of future earnings. In particular, Frankel and Lee (1998) and Dechow *et al.* (1999) show that using analyst forecasts, instead of forecasts based on past earnings, as a proxy for future expected earnings substantially improves the abilities of residual income valuation models to predict firms' intrinsic values. In addition, Cheng (2005) suggests that the usefulness of analyst forecasts stems from their ability to convey truthful forward-looking information that helps assess and predict firms' current and future performance.

However, analyst forecasts are subject to management's manipulation. For instance, Laurie P. Cohen, a staff reporter at the *Wall Street Journal,* wrote that, "…, chief financial officers or investor relations representatives traditionally give 'guidance' to analysts, … they are encouraging analysts to deflate earnings projections to artificially low levels." Academic literature provides further empirical evidence for this claim. For example, Cotter et al. (2006) find that analysts quickly revise their earnings forecasts in direct response to management guidance. In particular, the majority of analyst activity takes place in direct response to explicit management communications. In related studies, Richardson *et al.* (1999) and Bartov *et al.* (2002) document a decline in analyst forecasts from the beginning to the end of the year. They relate this phenomenon to the presence of expectations management. A related research question that arises from these studies is why firms seemingly issue downward earnings guidance.

Prior research provides some clues to answering this question. In particular, Kaznik and Lev (1995) find that firms facing earnings disappointments are more likely to issue earnings guidance to warn investors about the bad news and align market expectations with the firms' true profit prospects. In addition, Skinner (1994) argues that firms make pre-emptive bad news disclosures to minimize legal liability and reputation costs. However, more recent studies on expectations management argue that firms issue downward guidance for the purpose of dampening analysts' expectations and producing beatable forecasts. For instance, Bartov *et al.* (2002) and Matsumoto (2002) show that firms purposefully guide analyst expectations down to produce beatable forecasts by the end of the year. Also, Bernhardt and Campello (2007) argue that management guides analyst forecasts down, especially near earnings announcement, but such guidance cannot be attributed to the arrival of new information.

If firms guide analyst forecasts down for the purpose of misleading investors and producing beatable forecasts, then expectations management activities should introduce error into analyst forecasts and reduce the abilities of these forecasts to proxy future expected earnings; consequently, valuation models estimated using manipulated forecasts may have less ability to predict firms' true intrinsic values. This argument can be stated more formally in the following hypothesis:

H1: Expectations management for the purpose of BME introduces error in analyst forecasts and reduces the usefulness of analyst forecasts in firm valuation; consequently, intrinsic value metrics estimated using manipulated forecasts will have less ability to predict firms' true intrinsic values.

In the remainder of this chapter, I test this hypothesis and examine the impact of expectations management on firm valuation.

2.3 Research Design

In this section, I develop a measure for expectations management and use it to identify firms that manipulated analyst expectations to MBE (expectations manipulators) and the firms that did not manipulate analyst expectations (expectations non-manipulators). Then I use Ohlson's (1995) residual income valuation model as the valuation framework to estimate intrinsic value metrics. Next I describe the analyses used to examine the performances of the intrinsic value metrics estimated using manipulated versus non-manipulated forecasts to predict firm values.

2.3.1. Expectations Management Measure

Whether or not a firm has guided analysts to issue relatively low forecasts to MBE is inherently unobservable. Prior research has developed two main approaches to identify expectations management. In the first approach, advocated by Richardson *et al.* (1999) and Bartov *et al.* (2002), forecast guidance is suspected when analyst forecasts are optimistic at the beginning of a period and pessimistic at the end of the period. This approach identifies both the motive to manipulate (in the form of initial optimism) and the result of manipulation (in the form of downward revision in analyst forecasts). However, it has several unappealing features. First, this approach identifies only firms that MBE as manipulators, while erroneously classifying as non-manipulators firms that did manipulate but failed to guide forecasts down to a sufficiently low level to produce a positive forecast error. Second, the optimistic-then-pessimistic forecast pattern may simply be caused by bad news that arises during the year rather than by management's intentional downward guidance. Since this approach does not distinguish between these two scenarios, it can misclassify analyst reactions to bad news as expectations manipulation.

Taking a different approach, Matsumoto (2002) calculates an expected forecast using prior seasonal changes in earnings and cumulative returns during the year, and defines expectations manipulators as firms whose last consensus analyst forecasts are lower than the expected forecasts. The strength of this approach is that it identifies expectations manipulators regardless of whether or not they successfully MBE. In addition, it takes into account the effect of economy-wide and/or firm-specific bad news on analyst forecasts. However, a drawback of this approach is that it mechanically classifies all firm-years with last consensus forecasts lower than expected forecasts as expectations manipulators without considering whether there are downward revisions in analyst forecasts. In particular, Matsumoto's (2002) approach can misclassify firm-years with upward forecast revisions (evidence against expectations management) as expectations manipulators.

The above discussion suggests that, while each approach has its strengths and weaknesses, neither provides an accurate measure of expectations management for the purpose of MBE. In principle, a good measure of expectations management should be able to: (i) establish that there is a motive to manipulate expectations; (ii) identify evidence of downward forecast guidance; and (iii) control for alternative explanations for the observed downward guidance.

In this section, I develop a more precise measure of expectations management for the purpose of MBE that attempts to meet the above criteria. First, I define analyst forecast-related measures as follows. Forecast year *t* starts from 360 days prior to the announcement of year *t*'s earnings and ends at 1 day prior to the announcement. It consists of 12 forecast months, each of which represents a 30-day period. To avoid the staleness problem often associated with the consensus forecasts published by the Institutional Brokers' Estimate System (IBES), as documented by Richardson *et al.* (1999), I use the last forecast issued by each analyst within each time interval to compute the consensus forecast for that time interval. In particular, I define the monthly consensus forecast (AF_{itm}) as the median of the latest forecast issued by each analyst for firm *i* in month *m* of year *t*. Next, I define the early consensus for firm *i* in year *t* (AF_{it}^{early}) as the median of the latest forecast issued by each analyst for firm *i* in the first three months of year *t*, and the late consensus for firm *i* in year *t* (AF_{it}^{late}) as the median of the latest forecast issued by each analyst in the last three months of year *t*. Finally, I use the following two steps to classify a firm-year as either an expectations manipulator or a non-manipulator.

Step 1: Is there any identifiable motive/incentive to manipulate?

Bartov *et al.* (2002) identify initial analyst optimism as the necessary condition for concluding expectations management. The rationale for this argument is that if a firm's management believes at the beginning of the year that the existing forecasts are rationale and beatable, they perceive that there is no need to manipulate expectations down to MBE. However, Bartov et al.'s approach involves using forward-looking earnings information that is unavailable at the beginning of the year. To avoid this shortcoming, I use the previous year's reported earnings ($Earn_{it-1}$) as a proxy for management's earnings expectation at the beginning of the current year (MF_{it}^{early}).To the extent that a firm's performance does not change dramatically overnight, the previous year's earnings arguably represent a reasonable proxy for the current year's earnings at the beginning of the year. Furthermore, Degeorge *et al.* (1999) find that firms perceive "avoiding earnings decrease" as a more important threshold than MBE. This suggests that firms will be motivated to manipulate analyst forecasts down to MBE only if they can exceed the prior year's earnings. Therefore, I identify each firm's motive to manipulate analyst expectations by comparing the previous year's earnings ($Earn_{it-1}$) with the consensus forecast in the early period (AF_{it}^{early}). I then classify firms with $AF_{it}^{early} > Earn_{it-1}$ as possible manipulators and the remaining firms as non-manipulators.

Step 2: Is there any evidence of management-guided downward forecast revisions?

Downward revisions in analyst forecasts represent indirect evidence for management forecast guidance. However, expectations management is only one of the factors that can lead to downward revisions in analyst forecasts. This second step is designed to control for downward revisions caused by factors other than expectations management. These other factors include (i) analyst bias and (ii) unexpected economy-wide and/or firm-specific good/bad news that arises throughout the year. To elaborate on the first factor, Richardson *et al.* (1999) argue that analysts balance their need to please management against their need to please investors. In particular, they please management by issuing optimistic forecasts at the beginning of the year, which project good images to the market about firms' future performances. They please investors by producing accurate forecasts just prior to earnings announcements, when forecast accuracy is most salient. This suggests that some of the downward revisions in analyst forecasts may result from analyst bias rather than from expectations management. In this chapter, I use a regression-based method to control for revisions caused by the two alternative factors. Specifically, I consider the regression model

$$Rev_{it} = b_0 + b_1 CRET_{it} + v_{it}, \tag{2.1}$$

where the v_{it} are identically and independently distributed random error terms with mean 0 and variance σ_v^2; Rev_{it} is the change in analyst consensus forecasts from the beginning to the end of the year, i.e., $AF_{it}^{late} - AF_{it}^{early}$; and $CRET_{it}$ is the cumulative return for firm *i* during year *t*. In (2.1), I use the intercept term to capture analysts' general tendency to be optimistic and the cumulative return during the year, and $CRET_{it}$, to account for the impacts of economy-wide and/or firm-specific news on analyst forecast revisions. I estimate this regression for each year and use the residual from the regression as a measure for the unexpected forecast revision ($UnExpRev_{it}$). Then, I classify firm-years with unexpected downward revisions ($UnExpRev_{it} < 0$) as possible manipulators and the remaining firm-years as non-manipulators. Finally, I define expectations manipulators as firm-years that are classified as possible manipulators in both Step 1 and Step 2.

In Section 2.4.2., I conduct a validity test to demonstrate the validity of my measure and compare its performance with the performances of other existing measures at detecting management forecast guidance.

2.3.2. Residual Income Valuation Model

I use Ohlson's (1995) residual income valuation model as the valuation framework to estimate intrinsic value metrics. Ohlson (1995) starts with the dividend-discounting model, which states that the market value of a firm's equity (V_{it}) at year t equals the present value of expected dividends (d_{it}) discounted at rate r

$$V_{it} = \sum_{\tau=1}^{\infty} E_t(d_{it+\tau})/(1+r)^{\tau} \tag{2.2}$$

He also assumes a clean-surplus relation

$$b_{it} = b_{it-1} + x_{it} - d_{it}, \tag{2.3}$$

where b_{it} is the beginning of period t accounting book value of shareholders' equity and x_{it} is period t earnings. The clean-surplus assumption allows him to substitute book value and abnormal earnings for dividends in the dividend-discounting model. Ohlson (1995) defines the other information variable as the difference between the conditional expectation of abnormal earnings based on all available information ($E_t[x_{it}^a]$) and the expectation of abnormal earnings based only on last period abnormal earnings (ωx_{it-1}^a). That is,

$$v_t = E_t[x_{it}^a] - \omega x_{it-1}^a. \tag{2.4}$$

Ohlson further assumes linear information dynamics (LID) for the time-series behaviour of abnormal earnings

$$x_{it}^{a} = \omega x_{it-1}^{a} + v_{it-1} + u_{1it} \tag{2.5}$$

and other information

$$v_{it} = \gamma v_{it-1} + u_{2it}\,. \tag{2.6}$$

LID allow him to express firm value as a function of book value, abnormal earnings and other information

$$V_{it} = b_{it-1} + \alpha_1 x_{it-1}^{a} + a_2 v_{it}\,, \tag{2.7}$$

where $\alpha_1 = \omega/(1 + r - \omega)$ and $\alpha_2 = (1 + r)/(1 + r - \omega)(1 + r - \gamma)$.

A model introduced subsequently by Feltham and Ohlson (1995) retains the basic structure of the original model in Ohlson (1995). However, it breaks down both income statements and balance sheet components into their operating and financing activities to separately assess how they affect firm value. It then makes LID assumptions for abnormal operating earnings, operating assets, and other information to express firm value in terms of book value, operating assets, abnormal operating earnings, and other information. One advantage of this model is that, by separately modeling operating and financial assets, the model allows for accounting conservatism (*i.e.*, the market value and book value of operating assets can be different).

Whether the model proposed by Ohlson (1995) or the subsequent model introduced by Feltham and Ohlson (1995) performs better in estimating firm value is currently an unresolved issue in the valuation literature. For instance, in comparing the performances between the two models, Hand (2001) argues that, "though conservatism seems to be a pervasive attribute of U.S. GAAP, it may be the case that conservatism has an immaterial impact on the mapping of accounting data into price. It is unclear if a model that takes growth and conservative recognition into account fits the data significantly better than does the Ohlson 1995 [model]". It is important to stress that the objective of this chapter is not to compare the empirical performances of these valuation models. Rather, it is to use a valuation model as a framework to examine the usefulness analyst one-year-ahead forecasts in firm valuation. With this in mind, I choose the original model in Ohlson (1995) over the model in Feltham and Ohlson (1995) because the empirical implementation of "other information" in Ohlson's model (1995) requires only one-year-ahead forecasts (Dechow *et al.*, 1999), while the implementation of Feltham and Ohlson's (1995) model requires forecasts for both one- and two-year-ahead earnings (see Begley and Feltham, 2002). Obviously the quality of both types of forecasts has implications for the model's performance, but given that managers may manipulate current-year and longer-term forecasts differently, it is difficult to separately measure the effect of one while controlling for that of the other. Since my study in this chapter focuses on manipulation of current-year forecasts, using Ohlson's (1995) model provides a cleaner setting in which to investigate the issues of interest to this chapter.

I estimate Ohlson's (1995) valuation model using analyst forecasts to obtain monthly intrinsic value metrics (V_{itm}). Specifically, following Dechow *et al.* (1999), I use the monthly consensus analyst forecast (AF_{itm}) to estimate expected abnormal earnings

$$E_t[x^a_{itm}] = AF^a_{itm} = AF_{itm} - rb_{it-1} \tag{2.8}$$

and express the other information variable as

$$v_{itm} = AF^a_{itm} - \omega_t x^a_{it-1}. \tag{2.9}$$

Thus, the monthly intrinsic value metrics can be expressed as

$$V_{itm} = b_{it-1} + \alpha_1 x^a_{it-1} + \alpha_2 v_{itm}, \tag{2.10}$$

where $\alpha_1 = \omega_t / (1 + r - \omega_t)$ and $\alpha_2 = (1 + r) / (1 + r - \omega_t)(1 + r - \gamma_{tm})$. In this expression, ω_t and γ_{tm} are the first-order autoregressive coefficients for abnormal earnings and other information respectively. The parameter ω_t is estimated for each year *t* using the prior five years' data in the pooled time-series cross-sectional regression

$$x_{it}^a = \omega_0 + \omega_t x_{i,t-1}^a + u_{i,t}, \tag{2.11}$$

and the parameter γ_{tm} is estimated for each year-month (*t*,*m*) using the prior five years' data in the pooled time-series cross-sectional regression

$$v_{i,t,m} = \gamma_0 + \gamma_{tm} v_{i,t-1,m} + u_{2,t}. \tag{2.12}$$

Frankel and Lee (1998) use a fixed rate of 12% as the cost of capital (*r*). They explain that the choice of cost of capital (either a fixed rate of 12% or the industry-specific cost of capital estimated from the Fama and French three-factor model) has little effect on their cross-sectional analysis. In addition, Lee *et al.* (1999) argue that a time-varying cost of capital is crucial in time-series analysis. Therefore they compute the time-varying cost of capital as the sum of a time-varying risk free rate, and a consistent premium above that risk free rate. They find that the variations in risk premium (either a fixed rate or the industry-specific premium) do not impact their result. Since my study employs a time-series analysis, I follow Lee *et al* (1999) to compute the cost of capital as a sum of the monthly risk free rate and a fixed risk premium. The risk premium used by prior studies range from 3%-8%. In this study, I use a lower end of 3% in the main analysis. As a sensitivity analysis, I conduct the stock tracking ability test using the intrinsic value metrics estimated with a risk premium of 8%. The results, as reported in

Panel B of Table 3 and Panel B of Figure 1, demonstrate that the choice of risk premium does not affect inferences in the main analysis.

2.3.3. Testing the Performance of the Valuation Model to Track or Predict Firm Value

Prior research, such as Frankel and Lee (1998) and Lee *et al.* (1999), has examined the performance of the valuation models by testing the ability of intrinsic value metrics to track stock prices and predict future returns.

It is clear that the extent of market efficiency has implications for the choice of tests for stock tracking ability. Specifically, if the market is efficient in the short run, in the sense that stock price correctly reflects the true intrinsic value at all times, then intrinsic value metrics that most closely track stock prices are more accurate proxies for intrinsic value. In this case, the ability of valuation models to predict intrinsic value can be assessed by examining the correlations between intrinsic value measures (calculated from these valuation models) and stock prices. With the exception of Lee *et al.* (1999), most research has invoked the efficient market hypothesis as a maintained assumption and examined valuation models in this cross-sectional approach. Taking a different perspective, Lee *et al.* (1999) argue that the market may not be fully efficient at all times because the process by which price adjusts to intrinsic value requires time. In particular, arbitrage costs in the short run may prevent price from converging to the intrinsic value instantaneously; however, in the long run, market forces drive the price to the fundamental. Lee *et al.* (1999) find that it takes on average 3-4 months for stock price to converge to intrinsic value. The market that meets this description is said to be long-term efficient. If the market is long-term efficient, then stock price is not the best proxy for intrinsic value and, thus, it is inappropriate to assess intrinsic value metrics by their contemporaneous correlations with stock prices. To construct an appropriate test in this case, Lee *et al.* (1999) model the time-series relation between price (*P*) and true intrinsic value (V*) as a co-integrated system:[1]

$$\log(P_t) = \log(V_t^*) + \varepsilon_t \qquad (2.13)$$

Similarly, they model the time-series relation between intrinsic value (V) and true intrinsic value (V*) as a co-integrated equation:

$$\log(V_t) = \log(V_t^*) + \omega_t \, . \qquad (2.14)$$

In this framework, a good intrinsic value metric V_t would have a zero mean error term ($\omega_t = 0$), a low standard deviation, and quick mean reversion. Since the true intrinsic values V_t^* are unobservable, they consider the difference between (2.13) and (2.14),

$$\log(V_t / P_t) = \omega_t - \varepsilon_t \quad . \qquad (2.15)$$

In this alternative form, the time-series properties of error ε_t are set by market forces and the properties of the V/P ratio depend on those of ω_t. Lee *et al.* (1999) examine the time-series properties (in particular, the stationarity) of the V/P ratio to assess the usefulness of analyst-based value metrics (V), expecting better intrinsic value estimates to yield V/P ratios that have lower standard deviations and faster rates of mean-reversion. In the context of my study, I expect expectations management to reduce the ability of the intrinsic value metrics V to predict the true intrinsic values. That is, I expect the V/P

[1]If two or more time series are themselves non-stationary, but a linear combination of them is stationary, then the time series are said to be co-integrated (see Lee *et al.*, 1999).

ratios for intrinsic value metrics V estimated using manipulated forecasts to be less stationary (*i.e.*, with higher standard deviations and slower rates of mean-reversion) than those for intrinsic value metrics V estimated using non-manipulated forecasts.

To date, the extent of market efficiency (*i.e.*, how long it takes price to converge to intrinsic value) is an unresolved issue. To ensure that my results do not depend on any particular assumption about market efficiency, in this chapter I conduct both cross-sectional and time-series analyses to see whether consistent inferences can emerge from this exercise. Assuming that expectations management impairs firm valuation, I predict that, if the market is efficient in the short run, intrinsic value metrics estimated using manipulated forecasts will have lower correlations with stock prices. On the other hand, if the market is long-term efficient, I predict that intrinsic value metrics estimated using manipulated forecasts will yield V/P ratios with more volatile and more persistent time series.

The V/P ratio portfolio returns test also relies on the assumption of long-term market efficiency. In particular, if the market is not fully efficient at all times but stock prices converge to true intrinsic values over the course of a few months, then good intrinsic value metrics will be able to identify short-run mispricing and predict future returns over the long-run as the market corrects itself. If expectations management diminishes the quality of analyst forecasts as inputs for constructing intrinsic value estimates, we should observe that V/P ratios estimated with manipulated forecasts are less able to predict future returns than V/P ratios estimated with non-manipulated forecasts. Therefore, in the return predictability analysis, I examine whether the V/P ratio-based portfolio strategies, where V is estimated using non-manipulated forecasts, have greater predictive power for future returns than the V/P ratio-based portfolio strategies where V is estimated using manipulated forecasts.

2.4 Empirical Analyses

In this section, I examine the impact of expectations management on firm valuation by comparing the abilities of intrinsic value metrics estimated using manipulated and non-manipulated forecasts to track stock prices and predict future returns.

2.4.1 Data Collection and Sample Statistics

The sample consists of non-financial and non-regulated U.S. firms for the time period from 1988 to 2005. The descriptive statistics in the sample selection process are reported in Table 1. I obtain analyst forecasts and the corresponding actual EPS data from the IBES History U.S. Edition tape (Actual File) through the Wharton Research Data Services (WRDS) database. This results in 14,335 firms and 88,600 firm-years for the period. I then match this sample to the Center for Research in Security Prices (CRSP) database and Compustat. Matching from IBES to CRSP through CUSIP and deleting non-matches and duplicates reduces the sample to 11,414 firms and 71,497 firm-years. Matching from CRSP to Compustat through CUSIP to obtain GVKEY (the Compustat unique identifier) further reduces the sample to 10,707 firms and 67,669 firm-years. Richardson *et al.* (1999) and Matsumoto (2002) exclude regulated and financial firms because their accounting rules differ from those of firms in other industries and they may therefore have different motives with respect to expectations management. Following this practice, I exclude these firms from my sample. This reduces the sample to 6,992 firms and 46,043 firm-years. Requiring firm-years to have sufficient data to compute the expectations management measure further reduces the sample to 5,535 firms and 30,223 firm-years. I then randomly select 20% of the total firm-years to use as the validation sample to test my expectations management measure, and use the remaining 80% of the firm-years as the test sample to conduct the cross-sectional, time-series, and returns predictability analyses.

In the cross-sectional analysis, where I examine the change in correlations between prices and intrinsic value metrics from the beginning to the end of the year, I require the observations to have valid intrinsic value metrics at the beginning and the end of the year. This data requirement reduces the final test sample from 5,272 firms and 24,179 firm-years to 4,834 firms and 22,190 firm-years.

In the time-series analysis, where I examine the within-year time-series properties of bi-monthly V/P ratios, I require the firm-year observations to have valid intrinsic value estimates (V) in each of the six two-month intervals. This requirement reduces the usable test sample to 3,436 firms and 13,729 firm-years. Note that I do not require firms to have valid intrinsic value estimates at every month because doing so would result in a significant sample reduction, from 4,834 firms and 22,190 firm-years to 2,219 firms and 8,514 firm-years.

2.4.2 Validation of the Expectations Management Measure

This validity check is intended to examine whether my expectations management measure, which is based on indirect evidence of expectations management, has power to detect management forecast guidance. Management provides forecast guidance mainly through public management earnings forecasts; this has been especially true since the passage of Regulation Fair Disclosure (Reg FD), which prohibits firms from communicating private information with analysts. First Call maintains a dataset of prospective earnings-related announcements made by companies after September 1990. In this database (referred to as CIG), the "CIGCODED" field indicates whether the guidance is classified as negative, positive or neutral. A negative classification indicates that the management forecast is below the current expectation, providing evidence for downward forecast guidance. A non-negative classification indicates that the management forecast is at or above the current expectation, providing evidence against downward forecast guidance. Since forecast direction provides direct evidence for forecast guidance, management forecasts can be used to identify expectations management. However, out of the 6,044 firm-years in the validation sample, only 644 (or 11%) have management forecast data in the CIG database. Due to the sparseness of management forecasts and the resulting significant restriction in sample size, in this study I choose to identify expectations management based on the pattern of analyst forecast revisions as described above in Section 2.3.1. To validate my expectations management measure, I select from my validation sample the firm-years that have management guidance data in the CIG database. To compare my measure to the existing measures, I apply the classification schemes of Bartov *et al.* (2002) and Matsumoto (2002) to my sample.

A comparison of these three alternative expectations management measures is shown in Panel A of Table 2. My approach classifies 25% of the 644 CIG observations as expectations manipulators, while Bartov *et al.*'s approach classifies 28% as manipulators and Matsumoto's approach classifies 41% as manipulators. Note that, compared to the other two approaches, Matsumoto's approach classifies significantly more observations as manipulators. This is potentially because Matsumoto's approach does not require firms to demonstrate initial optimism or downward forecast revisions in order to be classified as manipulators. Bartov *et al.*'s approach classifies more firm-years as manipulators than my measure does. This is potentially because, when using downward revisions as evidence for forecast guidance, Bartov *et al.*'s approach does not control for the fact that some of the downward revisions are due to analysts' systematic bias and/or bad news occurred during the year.

To compare the abilities of the alternative classification approaches to capture the notion of expectations management, I examine their effectiveness at detecting management's direct actions to guide analyst forecasts. If an expectations management classification approach is able to capture management forecast guidance, then we expect that the classified manipulators to be more likely than the classified non-manipulators to have downward management guidance (evidence for expectations management) and less likely to have upward/neutral management guidance (evidence against expectations management).

I compare the three alternative approaches according to this criterion. The results are shown in Panel B of Table 2.

The firm-years that my approach classifies as expectations manipulators are 130% more likely than those my approach classifies as non-manipulators to have downward management guidance and 33% less likely to have upward/neutral guidance.[2] The chi-square statistic of 42.5 suggests that this group difference is statistically significant. This provides evidence to support the ability of my approach to capture direct evidence of management forecast guidance. In comparison, using Bartov *et al.*'s approach, the expectations manipulators are 112% more likely than the non-manipulators to receive downward management guidance and 29% less likely than the non-manipulators to receive upward/neutral management guidance; whereas using Matsumoto's approach, expectations manipulators are 119% more likely than the non-manipulators to receive downward management guidance and 26% less likely than the non-manipulators to receive upward/neutral management guidance. Although Matsumoto's and Bartov *et al.*'s approaches both show the correct pattern, in the sense that the classified manipulators are more likely than the non-manipulators to receive downward management guidance and less likely to receive upward/neutral guidance, their results are weaker than mine (*i.e.*, 130% *vs.* 112% *vs*. 119% and -33% *vs*. -29% *vs*. -26%). This is also evident by their smaller chi-square statistics (34.5 and 36.7 respectively). Taken together, these results provide evidence that my measure captures management action to guide forecasts downward, and does so better than the existing measures. However, it is worth noting that, unlike my classification approach, the direction of management forecast obtained from the CIG database does not adjust the direction of guidance by the contemporary good/bad news contained in management forecasts. Consequently, my classification approach does not align perfectly with the direction of management forecast guidance reported in the CIG database. For instance, about half of the firm-years that I classify as

[2] Note that if the classified manipulators are more likely to have downward forecast guidance, they will by definition be less likely to have upward/neutral forecast guidance; the downward and upward/neutral guidance statistics are two statistics from the same validation test, rather than two distinct validations.

expectations manipulators actually have upward or neutral management forecasts before controlling for the good/bad news contained in these forecasts. Therefore, examining the directions of management forecasts from the CIG database is not a perfect validation test, though it does provide some evidence about the relative performances of the alternative classification approaches.

2.4.3 Stock Tracking Ability—Cross-sectional Analysis

In the cross-sectional analysis, I assume that the market is efficient at all times and that stock price is the best proxy for intrinsic value (see Frankel and Lee, 1998). Therefore, better intrinsic value metrics have higher correlations with stock prices. Furthermore, if the market can recognize firms' intentional manipulation of analyst forecasts, then stock prices will not change in the direction of forecast revisions if these revisions are due to management manipulation. Consequently, the intrinsic value metrics estimated using manipulated forecasts will diverge from the stock prices once manipulation occurs. I therefore predict that the correlations between prices and intrinsic value estimates for the manipulators will decline from the beginning of the year (before manipulation has occurred) to the end of the year (after expectations management has occurred and has been recognized by the market). However, I expect no systematic decline in the correlations for the non-manipulators because there should be no systematic divergence between intrinsic value estimates and stock prices in the absence of expectations management. Therefore, I examine and compare the changes in the cross-sectional sample correlations between prices and intrinsic value estimates for expectations manipulators and non-manipulators from the beginning to the end of the manipulation year.

I first graph the monthly sample correlations for the manipulators and non-manipulators throughout the year to see whether there is, as predicted, a decline in correlations for the manipulators and an absence of decline for the non-manipulators. For each group in each year *t* and month *m*, I compute the monthly cross-sectional sample correlations between the monthly intrinsic value metrics (V_{itm}) and the stock prices at the end of each month (P_{itm}). I then compute the across-year means of these annual monthly cross-sectional sample correlations. I graph in Figure 1 these mean monthly sample correlations for the manipulator and non-manipulator groups to depict the correlation patterns from the beginning to the end of the year. As mentioned earlier, to demonstrate that the choice of the risk premium in estimating the intrinsic value metrics does not affect inferences about the intrinsic value metrics, I estimate the intrinsic value metrics using two alternative risk premiums: 3% and 8%. I report monthly sample correlations between prices and intrinsic value metrics estimated using a 3% risk premium in Panel A of Figure 1, and between prices and intrinsic value metrics estimated using an 8% risk premium in Panel B. As shown in Panel A of Figure 1, the correlation patterns differ between the manipulator and non-manipulator samples in the manner predicted. For the manipulators, the sample correlations decline sharply in the middle of the year (presumably when expectations management occurs and is recognized by the market), whereas non-manipulators show no apparent decline in sample correlations from the beginning to the end of the year. Note that the pattern in Panel B mirrors that in Panel A, providing evidence that the choice of the risk premium does not affect our inferences. To further examine whether these correlation changes are statistically significant, I conduct the following test: for each group, I use the consensus analyst forecast in the first three months of the year (AF_{it}^{early}) to estimate the intrinsic value metrics at the beginning of the year (V_{it}^{early}). I then use V_{it}^{early} and the stock prices at the end of the third month (P_{it}^{early}) to compute the cross-sectional sample correlations between V and P for each group at the beginning of each year. I denote these early correlations by $Corr_{it}^{early}(P,V)$. Similarly, I use the consensus analyst forecast in the last three months of the year (AF_{it}^{late}) to compute the intrinsic value metrics at the end of the year (V_{it}^{late}). I then use V_{it}^{late} and the stock prices at the end of the twelfth month (P_{it}^{late}) to compute the cross-sectional sample correlations between V and P at the end of the year. I denote these late correlations by $Corr_{it}^{late}(P,V)$. I report the annual statistics on $Corr_{it}^{early}(P,V)$ and $Corr_{it}^{late}(P,V)$ in Table 3. The last row, "All years", reports the means of these annual statistics across all years. The *t*-statistics are based on the time-series standard errors of the annual statistics. Again, intrinsic value metrics are estimated using two alternative risk premiums of 3% and 8%. Panel A reports results using a 3% risk premium and Panel B reports results using an 8% risk premium. As shown in Panel A, across all years, the sample correlations for the manipulators decline from 0.55 at the beginning of the year to 0.49 by the end of the year. This total decline of 0.06 is statistically significant at the 5% level (with a t statistic, t = -2.04). In contrast, there is no systematic decline in sample correlations for the non-manipulators from the beginning to the end of the year. The average sample correlation is 0.56 at both the beginning and the end of the year. At the beginning of the year, there is no significant difference in sample correlations between the manipulators and non-manipulators (0.55 versus 0.56 with t = 0.53). The difference in sample correlation changes between the manipulator and non-manipulator groups is therefore −0.06. This difference is statistically significant at the 5% level (with t = -3.07). Results in Panel B are consistent with those in Panel A, providing evidence that the choice of risk premium does not affect inference in the cross-sectional test.

Overall, the significant decline in monthly correlations between stock prices and intrinsic value metrics estimated using manipulated forecasts and the lack of decline in correlations for intrinsic value metrics estimated using non-manipulated forecasts point to the negative impact of expectations management on the abilities of intrinsic value metrics to track stock prices. These results show that the market can recognize and discount for expectations management at least in the long-run over a 9-month interval; they, therefore, provide evidence in support of long-term market efficiency with respect to expectations management.

2.4.4 Stock Tracking Ability—Time-series Analysis

In the time-series analysis, I examine the within-year time-series properties (*i.e.*, standard deviation and the first-order autocorrelation) of bi-monthly V/P ratios for the manipulators and non-manipulators. Since requiring the firm-year observations to have valid intrinsic value metrics in each month significantly reduces the sample size, I relax this requirement by estimating intrinsic value metrics in every two-month interval. Specifically, I partition each forecast year into six two-month intervals and estimate intrinsic value metrics at the end of every two months. These bi-monthly intrinsic value metrics are estimated using bi-monthly consensus forecasts, each of which is calculated as the median of the latest forecast issued by each analyst within every two-month period. I require each firm-year to have valid intrinsic value estimates in each of the six two-month periods. I then use these bi-monthly intrinsic value metrics to compute the bi-monthly V/P ratios for each group in each year as follows. I aggregate individual V and P estimates for each group to form the portfolio V and P estimates for each group at every two-month interval in each year (*i.e.,* $V^M_{m,y} / V^N_{m,y}$ and $P^M_{m,y} / P^N_{m,y}$). I then use these aggregate V and P estimates to compute the portfolio V/P ratio for each group in each two-month interval of each year (*i.e.,* $V / P^M_{m,y}$ and $V / P^N_{m,y}$).

Assuming that the market is efficient over a period of several months, better intrinsic value metrics will yield a more stationary V/P time-series with a smaller standard deviation and a quicker mean reversion (see Lee *et al.* 1999). If expectations management impairs firm valuation as hypothesized, then the within-year across-month time series of V/P ratios for V estimated using manipulated forecasts will be more volatile and more persistent than the time series of V/P ratios, where V is estimated using non-manipulated forecasts. I measure volatility by the standard deviation and measure persistence by the first-order autocorrelation coefficient of the bi-monthly V/P ratios.

Panels A and B of Table 4 report the annual bi-monthly V/P ratios along with the standard deviations and first-order autocorrelation coefficients of these V/P ratios for the manipulator and non-manipulator groups respectively. I take the means of these statistics across the 18 years (1988 to 2005) for each manipulation group and report these summary statistics in the last rows of these two panels. In Panel C of the table I report the differences in standard deviations and the coefficients of the first-order autoregressions for the manipulators and non-manipulators. The *t*-statistics reported in the last row of

Panel C are based on the time-series standard errors from the annual statistics. On average, the manipulators have larger standard deviations than the non-manipulators (0.04 versus 0.02), and this difference of 0.02 is statistically significant at the 5% level (with t = 6.58). The average value of the coefficients in the first-order autocorrelation processes for the bi-monthly V/P ratios across all years is 0.32 for the manipulator group and 0.26 for the non-manipulator group. The difference between these two groups, 0.06, is also statistically significant at the 5% level (with t = 2.34). This suggests that, for the non-manipulators, innovations to V/P time-series lose their intensity more quickly, so that V/P reverts back to its long run mean faster in the months subsequent to a deviation. Overall, these results show that the expectations manipulators have a more volatile and more persistent V/P time series than the non-manipulators do. Taken together, they provide consistent evidence in support of my working hypothesis that expectations management impairs the usefulness of forecasts in firm valuation and reduces the abilities of the resulting intrinsic value estimates to track stock price variations in the long run.

2.4.5. Return Predictability Analysis

As detailed earlier, assuming the market is efficient over the long-run, in the sense that price converge to the true intrinsic value in the course of a few months, better intrinsic value metrics will have greater abilities to identify temporary stock mispricing and predict future returns through V/P ratios. This is because stock prices may measure firms' fundamental values with error and good intrinsic value metrics can identify such security mispricing (see Dechow *et al.* 1999). If expectations management impairs firm valuation and reduces the ability of valuation models to predict firms' fundamentals, then intrinsic value metrics estimated using manipulated forecasts are less able to predict future returns than intrinsic value metrics estimated using non-manipulated forecasts. I replicate Dechow *et al.* (1999)'s V/P ratio portfolio strategy to examine the buy-hold returns for expectations manipulators and non-manipulators in the 12 months following expectations manipulation. Since according to my classification process, expectations management is identified in the last month of a forecast year, I use V estimated in the last month and examine how manipulators and non-manipulators differ in their abilities to predict future returns through V/P ratios.

To ensure that the sample firm-years are aligned in calendar time, I use firms that report in February as the sample for the returns test. To implement the test, for each manipulation group in each year, I rank firms by V/P ratio and assign them into quintiles. I then compute the equally-weighted buy-hold stock return for each quintile portfolio of each group over the subsequent 12 months. Assuming that V is a good proxy for intrinsic value, the top V/P quintile (*Q5*) consists of stocks that are underpriced relative to intrinsic value and are expected to experience higher future returns; the bottom V/P quintile (*Q1*) contains stocks that are overpriced and are expected to experience lower future returns. The hedge portfolio return, which is the difference between the returns for *Q5* and *Q1*, summarizes the predictive ability of V/P ratio with respect to future returns. I report the yearly and across-year average V/P quintile returns and hedge portfolio returns for the manipulators and non-manipulators in Panels A and B of Table 5. The *t*-statistics for the across-year average returns are computed from the standard errors of the annual statistics. In Panel C I report the differences in annual portfolio returns between the manipulator and non-manipulator groups. The last row of Panel C summarizes the across-year average return difference between the two groups. The *t*-statistics are computed from the standard errors of the annual statistics.

For the manipulators, the hedge portfolio return is -7% and this return is not statically significant (with t = -0.50); for the non-manipulators, the hedge portfolio return is 9% over a 12 month period and this return is statically significant at a 10% level (with t = 1.38). The difference in average hedge portfolio returns between manipulators and non-manipulators is therefore -16%; this return difference is statistically significant at the 5% level (with t = -3.98).

Overall, these returns results suggest that [i] the market is long-term efficient, in the sense that there is potential mis-pricing in the short-run but price converges to true intrinsic value over the long-run, and [ii] the intrinsic value metrics are able to identify short-term market mispricing and predict future returns through V/P ratios in the long-run; however, expectations management reduces the ability of intrinsic value metrics to identify stock mispricing and predict future returns through the V/P ratios.

2.5 Sensitivity Analyses

In this section, I perform sensitivity checks for the results obtained the main analyses.

2.5.1 Sub-period Analysis of the Cross-sectional Test

A closer look at the yearly cross-sectional results in Table 3 reveals that the correlation difference between manipulators and non-manipulators is most significant in 1998-2000, which coincides with the Internet bubble period. To ensure my overall result is not driven by this abnormal time period, I exclude these three years in this sensitivity analysis. The results show that after excluding the Internet bubble period, the difference in average correlation changes between manipulators and non-manipulators is 0.023, and statistically significant at the 5% level (with t = 1.98). This suggests that the difference in correlation changes between manipulators and non-manipulators as reported in the main analysis is not specific to the Internet bubble period.

2.5.2. Fama and French Returns Tests

In the returns analysis reported in Section 2.4.5, I replicated Dechow *et al.* (1999)'s V/P ratio portfolio strategy to examine the buy-hold returns for expectations manipulators and non-manipulators in the 12 months following expectations manipulation. My results suggested that intrinsic value metrics estimated using manipulated forecasts were less able to predict future returns than those estimated using non-manipulated forecasts. However, the documented difference in returns between manipulator and non-manipulator groups may have been attribiutable to the different risk characteristics between these two groups. In fact, Beaver (2002), Kothari (2001), and Lo and Lys (2000) express the concern that high V/P firms may have higher risks and, therefore, the returns to V/P ratio portfolio strategy may be caused by uncontrolled risk factors. To address the possibility that the difference in V/P ratio portfolio returns between the manipulator and non-manipulator groups are due to differences in risks between the two groups, I use the calendar-time approach Fama and French returns regression to control for risks and obtain risk-adjusted returns. I then compute the risk-adjusted V/P ratio portfolio returns and compare the return performances between the two manipulation groups.

To ensure that the sample firm-years are aligned in calendar time, I use the 1,478 firms and 4,307 firm-years that report earnings in February as my usable sample. I choose to use February, because compared to other months it has the most firms reporting. To implement the strategy, for each manipulation group in February of each year, I rank firms by V/P ratios and partition them into quintiles. I then obtain the monthly returns for each firm for the next 12 months. For each manipulation group, I compute the average monthly return for each V/P quintile ($Ret_{m,t}^{Qn}$). Specifically, $Ret_{m,t}^{Q5-M}$ represents the average monthly return to the top V/P quintile for the manipulator group in month *m* of year *t;* $Ret_{m,t}^{Q1-M}$ represents the average monthly return to the bottom V/P quintile for the manipulator group in month *m* of year *t;* $Ret_{m,t}^{Q5-N}$ represents the average monthly return to the top V/P quintile for the non-manipulator group in month *m* of year *t;* and $Ret_{m,t}^{Q1-N}$ represents the average monthly return to the bottom V/P quintile for the non-manipulator group in month *m* of year *t.*

I obtain the Fama and French risk factors and the momentum factor from the "Fama-French, Momentum, and Liquidity" dataset on the WRDS database. I then regress the monthly returns for the top and bottom V/P quintiles for each manipulation group on the risk factors as follows:

$$Ret_{m,t}^{Q5-M} = \alpha_{m,t}^{Q5-M} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q5-M} \tag{2.16}$$

$$Ret_{m,t}^{Q1-M} = \alpha_{m,t}^{Q1-M} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q1-M} \tag{2.17}$$

$$Ret_{m,t}^{Q5-N} = \alpha_{m,t}^{Q5-N} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q5-N} \tag{2.18}$$

$$Ret_{m,t}^{Q1-N} = \alpha_{m,t}^{Q1-N} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q1-N} \tag{2.19}$$

I use the estimated intercepts $\tilde{\alpha}_{m,t}^{Q5-N}$ and $\tilde{\alpha}_{m,t}^{Q1-N}$ as the risk-adjusted monthly quintile returns to the top and bottom V/P quintiles for the non-manipulator group. I then compute the risk-adjusted V/P ratio hedged portfolio return as the difference in the risk-adjusted quintile returns to the top and bottom V/P quintiles ($\tilde{\alpha}_{m,t}^{Q5-N}$ - $\tilde{\alpha}_{m,t}^{Q1-N}$). The t-statistics on the hedged portfolio returns are computed using the means and standard deviations of the two quintile returns. I report these risk-adjusted quintile returns and hedged-portfolio returns in Table 6.

Results on the individual quintile returns show that, for the non-manipulator group, the top V/P quintile is able to earn a significant positive return of 0.008 (with t = 2.66), while the return to the bottom V/P quintile is 0.004 and is not statistically significant at a 5% level (with t = 1.69). The hedge portfolio return, which is the difference in the risk-adjusted returns between the top and bottom V/P quintiles, is 0.004, and this return is statistically significant at a 5% level (with t = 4.20). This provides evidence to support the ability of the intrinsic value metrics for the non-manipulators to identify stock mispricing and predict future returns through V/P ratios. In contrast, for the manipulator group, both the top and bottom V/P quintiles are unable to earn abnormal returns after controlling for risks; that is, the returns of -0.003 and 0.006 are statistically insignificant at a 5% level (with t = 0.65 and t = 1.27 respectively). The difference in risk-adjusted returns between the top and bottom V/P quintiles is negative (-0.009) and statistically significant at 5% level (with t = -5.41). As mentioned earlier, if the intrinsic value metrics represents a good measure for firm value, I expect to see the return to the top V/P quintile to be higher than that to the bottom V/P quintile. This negative and significant return difference between the top and bottom V/P quintiles suggests that the intrinsic value metrics for the manipulators is not a good measure for firm value and it cannot identify stock mispricing and predict future returns. Overall, these returns result provide further evidence in support of the hypothesis that expectations management introduces errors into analyst forecasts and reduces the ability of accounting valuation models to predict firm value.

2.5.3. Imputed Discount Rate

In this validation test, I calculate the imputed discount rate for the two groups and examine whether the imputed rate is higher for the manipulator group than for the non-manipulator group. I use the following steps to compute the imputed cost of capital. First, I collect the data and construct the variables (except the cost of capital variable) used in the valuation model. I then solve for the implied discount rate that equates the estimated intrinsic value from the model to the current stock price. However, it is important to note that when equating price to intrinsic value estimate, we are making an implicit assumption that the valuation model is correct in pricing securities at all times. Strictly speaking, the assumption is tenuous in the context of my study. In fact, the results in the returns test of the main analyses suggest that stock price is *not* the best measure for value at all times. Instead, stocks are mispriced in the short-run, but price converges to true intrinsic value over the course of a few months. In addition, my results also show that the valuation model produces inaccurate estimates for firm value when expectations manipulation occurs. Therefore, it is logically incorrect to equate price to intrinsic value estimate to solve for *r*. To further demonstrate this point, I use the following formulas to equate price to intrinsic value estimates obtained from the Ohlson's (1995) model and solve for the imputed discount rate. First I equate price to intrinsic value metrics estimated from the model:

$$P_{it}^{m} = V_{it}^{m} = b_{it-1} + \frac{\omega}{1+r\omega}(x_{it-1} - rb_{it-2})$$

$$+\frac{1+r}{(1+r+\omega^{m})(1+r-\gamma^{m})}[AF_{itm} - rb_{t-1} - \alpha(x_{t-1} - rb_{t-2})] \quad (2.16)$$

Next I set

$$A = -P_{it}^{m}$$
$$B = (b_{it-1} - P_{it}^{m})(2+\omega-\gamma^{m}) + \omega\gamma^{m} b_{it-2} - b_{it-1} + AF_{itm}$$
$$C = (b_{it-1} - P_{it}^{m})(1+\omega-\gamma^{m}+\omega\gamma^{m}) - \omega\gamma^{m} x_{it-1} AF_{itm}.$$

Then, *r* can be expressed in terms of *A*, *B*, and *C* as follows:

$$r = \frac{-B \pm \sqrt{B^2 - 4AC}}{2A}$$

Computing *r* for each observation, I find that 75% of the observations have invalid *r* estimates (*i.e.*, $B^2 - 4AC < 0$). The manipulators are more likely to have invalid values than the non-manipulators; that is, around 80% of the manipulators and 70% of the non-manipulators have invalid *r* estimates. This provides evidence that [i] the market is long-term efficient and it is, therefore, incorrect to equate intrinsic value estimate to contemporary price to solve for *r* in the short-run, and [ii] the intrinsic value estimates for the manipulators have less ability to measure firm value than those for the non-manipulators.

2.5.4. Reputation Effect

Companies may establish reputations, either for manipulation or non-manipulation. This section examines the possibility that companies have either positive (consistent non-manipulators) or negative (consistent manipulators) reputations and the consequences of this reputation effect on firm valuation.

If a firm manipulated expectations in the previous year, the market will be more cautious about the accuracy of its forecasts in the current year. They will place less weight on these forecasts in security pricing. Consequently, the intrinsic value metric for repetitive manipulators (who manipulated in both the previous year and the current year and therefore have bad reputations) are expected to have lower ability to track stock price than intrinsic value metric for non-repetitive manipulators (who manipulated only in the current year). As in the main analyses, I assess stock tracking ability by [i] the cross-sectional correlation between intrinsic value estimates and stock price and [ii] the stationarity (volatility and persistence) of the V/P time-series.

Table 7 reports the classification statistics of the manipulators and non-manipulators in the current and prior years. Overall, 6,471 out of 24,691 firm-years (26.2%) are classified as manipulators in the current year. Of these 6,471 current-year manipulators, 1,418 (21.9%) manipulated forecasts in the prior year, and 3,488 (53.9%) did not manipulate forecasts in the prior year. The remaining 1,565 (24.2%) current-year manipulators do not have sufficient data to be classified as manipulators or non-manipulators in the prior year. Furthermore, of the 4,905 firm-years that manipulated forecasts in the prior year, 1,418 (28.9%) continue to manipulate forecasts in the current year and 3,487 firm-years (71.1%) do not manipulate forecasts in the current year. This suggests that firms that manipulate in the current year are no more likely to manipulate in the prior year or in the next year than firms that do not manipulate in the current year. We next examine the market reaction to the firms that do manipulate forecasts two years in a row.

I define repetitive manipulators (MM) to be the firm-years that are classified as manipulators in both the current year and the previous year. I define non-repetitive manipulators (MN) to be firm-years that are classified as manipulator in current year and non-manipulator in the previous year. I choose to use only one prior year to establish the reputation effect because there are very few firms that manipulate expectations three years in a row (in fact, only 447 firm-years, 1.81% of total firm-years, are manipulators for three consecutive years). To examine the reputation effect, I compare the performances of these two groups – repetitive manipulators (MM) and non-repetitive manipulators (MN) in the stock-tracking ability and returns predictability analyses.

2.5.4.1. Cross-sectional Analysis

In this analysis, I compare the sample correlation between price and intrinsic value metrics for repetitive and non-repetitive manipulators. Consistent with the reputation effect, I predict that repetitive manipulators will have a lower sample correlation at the beginning of the year and a greater decline in sample correlations throughout the year than non-repetitive manipulators. The result as reported in Table 8 shows that, at the beginning of the year, MM has lower sample correlations than MN (0.53 versus 0.56); however, this difference of 0.03 is not statistically significant (with t = -0.23); furthermore, MM and MN both experience a significant decline of 0.06 in correlations from the beginning to the end of the year, but the difference in correlation changes between the two groups is not statistically significant (with t = 0.19). Overall, these results do not provide evidence in support of the hypothesized reputation effect.

2.5.4.2 Time-series Analysis

In this analysis, I compare the time-series properties of V/P ratios for repetitive and non-repetitive manipulators. Consistent with the reputation effect, I predict that intrinsic value estimates for repetitive manipulators yield V/P ratios with greater volatility (as measured by sample standard deviation) and greater persistence (as captured by the estimate of the first-order autoregressive coefficient) than intrinsic value metrics for non-repetitive manipulators. In Panels A and B of Table 9 I report the V/P ratios and standard deviations and AR1s for the V/P ratios for the repetitive manipulators and non-manipulators respectively. In Panel C I report the differences in the sample standard deviations and the first-order autoregressive coefficient estimates for the two groups. As shown in Panel C, repetitive manipulators have higher sample standard deviations than non-repetitive manipulators (0.04 *vs.* 0.02) and this difference of 0.02 is statistically significant at the 5% level (with t = 3.68). In contradiction to the prediction, the estimate of the first-order autoregressive statistic is larger in magnitude for the non-repetitive manipulators than the repetitive manipulators (0.30 versus 0.26), but this difference of -0.04 is not statically significant at the 5% level (with t = -1.07). Therefore, the results from the time-series analysis provide no evidence in support of the hypothesized reputation effect.

2.5.4.3 Returns Analysis

In this returns test, I examine the return performance of MM and MN in the 12 months subsequent to current year's earnings announcement. I report the annual returns result and the cross-year averages of the returns for MM and MN in Table 10 Panel A and B for the manipulators and non-manipulators. The last row of these Panels summarizes the cross-year averages of returns. Panel C reports the difference in returns between the repetitive manipulators and non-repetitive manipulators. The *t*-statistic is computed from the standard errors of the annual statistics. As summarized in Panel C, the average V/P ratio portfolio return for the repetitive manipulators is -0.07 and that for the non-repetitive manipulators is 0.03. Comparing the returns performance of repetitive manipulator and non-repetitive manipulator subgroups with the returns performance for the overall manipulator group as reported in Table 5, we see that the repetitive manipulator subgroup earns similar returns to the overall manipulator group (-0.07 and -0.07), while the non-repetitive manipulator subgroup earns higher returns than the overall manipulator group (0.03 versus -0.07). The difference in portfolio returns for the repetitive and non-repetitive manipulators is 0.10, and this return difference is not statistically significant at the 5% level (with t = 0.68). These results therefore provide weak evidence in support of the hypothesized reputation effect.

In summary, the results from the stock-tracking ability test and the returns test provide, at best, only weak evidence in support of the hypothesized reputation effect that firms establish reputation for manipulation/non-manipulation.

2.6 Conclusion

In this chapter, I first build on prior research to develop an improved measure for expectations management; I then examine the impact of expectations management on firm valuation. Specifically, I examine and compare the performances of intrinsic value metrics estimated using manipulated versus non-manipulated forecasts to track stock price and predict future returns. Overall, the results suggest that, in the absence of expectations management, the market is long-term efficient and intrinsic value metrics represent good measures for firm value; consequently, intrinsic value metrics can identify short-term market mispricing and predict future returns through V/P ratios in the long-run when the market corrects its short-run mispricing. However, expectation management reduces the ability of intrinsic value metrics to identify stock mispricing and predict future returns through V/P ratios, but the market is efficient with respect to expectations management over the long-run, in the sense that it identifies and appropriately discounts for such manipulation. Consequently, V/P ratio portfolio strategies, where V is estimated using manipulated forecasts earns significantly lower return than the V/P ratio portfolio strategy, where V is estimated using non-manipulated forecasts. Taken together, these results provide evidence in support of the joint hypothesis of [i] long-term market efficiency with respect to expectations management and [ii] the negative impact of expectations management on the usefulness of analyst forecasts in accounting valuation models.

CHAPTER 3: THE IMPACT OF EARNINGS MANAGEMENT ON THE USEFULNESS OF EARNINGS IN FIRM VALUATION

3.1. Introduction

Many empirical studies, such as Teoh *et al.* (1998) and Erickson and Wang (1998), have documented the existence and extent of earnings management; however, little research has been conducted to date to investigate the consequences and implications of such manipulation. Observing ever increasing earnings management activities and accounting scandals, the SEC has expressed the concern that the pressure to meet earnings expectations may be eroding the quality of financial reporting. In this respect, Kasznik and McNichols (2002) call for inquiry into the consequences of management manipulation for firm valuation. In response to this, this chapter studies the impacts of earnings management on the usefulness of earnings in firm valuation.

Earnings are often used in firm valuation by both the stock market and accounting valuation models. Earnings are useful because they capture truthful information relevant in assessing and predicting firm performance. However, firms' deliberate earnings management activities may introduce errors into earnings and, thereby, reduce their ability to convey truthful information (Bernard, 1995). Earnings management reduces the usefulness of earnings and impairs the ability of accounting valuation models to predict firm value. The intrinsic value estimate will not be able to identify stock mispricing and predict future returns through a V/P-ratio portfolio strategy of buying under-priced stocks and selling over-priced stocks. However, whether or not the stock market is efficient with respect to earnings management is an empirical issue. If the market is efficient with respect to earnings management (*i.e.*, it can identify and appropriately discount for such manipulation), then in light of earnings management, the stock price is a more accurate measure of firm value than the intrinsic value estimate from the accounting valuation model. On the other hand, if the stock market can not identify and appropriately discount for earnings manipulation, and is more adversely affected by management manipulation than the accounting valuation model, then in the presence of earnings management, the stock price represents a less accurate measure for firm value than the intrinsic value estimate from the accounting valuation model. To investigate which is actually the case, I examine the returns from the V/P-ratio portfolio strategies for the manipulator and non-manipulator groups.

Results from the returns test show that the V/P ratio portfolio strategy for the non-manipulators can earn a significant and positive return, while the V/P ratio portfolio strategy for the manipulators is not able to predict future returns. These results provide evidence that in absence of earnings management, the intrinsic value metrics estimated from the accounting valuation model represents a good measure of firm value – it can identify stock mispricing and predict future returns through V/P ratios. However, earnings management reduces the ability of the accounting valuation models to predict firm value, but it impairs the stock market to a lesser extent. Consequently, in the presence of earnings management, the stock price represents a more accurate measure for firm value than the intrinsic value metrics from the accounting valuation model. In conclusion, these results provide evidence for the joint hypotheses of (1) the adverse impact of earnings management on the performance of accounting valuation models, and (2) the long-term market efficiency with respect to earnings management.

The rest of this chapter is organized as follows. Section 3.2 reviews related literature, Section 3.3 develops a measure for earnings management and presents the valuation model used to estimate intrinsic value metrics, Section 3.4 presents the empirical results on the impacts of earnings management on firm valuation, and Section 3.5 concludes.

3.2. Literature Review

3.2.1. Earnings Management

Healy and Wahlen (1999) state that "Earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting numbers."

It should be stressed that firms have many ways to manipulate earnings upward; for instance, they can use accounting discretion to [i] create income- increasing discretionary accruals (accrual manipulation) or [ii] take real economic steps, such as reducing discretionary spending on R&D, advertising, and maintenance, to boost earnings (real activity earnings management). Furthermore, there are multiple earnings benchmarks that firms attempt to achieve through earnings management. For instance, Burgstahler and Dichev (1997) show that firms manipulate earnings to avoid reporting losses and earnings decreases, and Degeorge *et al.* (1999) show that in addition to the positive earnings and positive earnings changes benchmarks, firms also manipulate earnings to meet or beat analyst expectations. It is therefore difficult (if not impossible) to use a single approach to capture all types of earnings management activities for all purposes. In this chapter, I design a specific measure to capture one particular type of earnings management for one particular purpose, which is accrual management to avoid reporting negative earnings.

3.2.2. Usefulness of Earnings in Firm Valuation

A survey paper by Graham *et al.* (2005) documents that CFOs believe that earnings, not cash flow, is the key metric considered by outsiders. The explanation for the focus on EPS is that the world is complex and the number of available financial metrics is enormous. At the same time, investors need a simple metric to summarize corporate performance. In particular, this metric has to be easy to understand and relatively comparable across companies, and EPS satisfies these criteria. Consistent with this view, Skinner and Sloan (2002) report that, in the stock market, investors regard earnings as an important benchmark to evaluate firm performance and they tend to severely punish firms that fail to meet earnings benchmarks.

In accounting research, earnings are also used as critical inputs to accounting valuation models. Residual income valuation models, such as Ohlson (1995), express firm value as a linear function of book value, residual earnings, and other information. Prior studies examining the empirical implementations of this model, in particular Dechow *et al*. (1999), show that the estimated intrinsic value metrics represent good measures for firm value; that is, they can identify potential stock mispricing and predict future returns through a V/P ratio portfolio strategy of buying under-valued stocks and selling over-valued stocks. Earnings are useful in accounting valuation models because they can capture truthful information about firm performance. However, Bernard (1995) argues that one drawback of using earnings in valuation is that they contain “noise” and, being susceptible to management manipulation, they may not accurately reflect firms’ true performances.

The above review suggests that earnings manipulation may introduce errors into earnings and thereby reduce the ability of these earnings numbers to reflect or predict firm performances; this in turn may diminish the abilities of the accounting valuation models to accurately predict firms’ intrinsic values. Therefore, I hypothesize that

H2: Earnings management introduces errors in earnings and reduces the usefulness of earnings in firm valuation; consequently, intrinsic value metrics estimated using manipulated earnings will have less ability to predict firm value.

3.3. Research Design

In this section, I develop the measure for earnings management and present the process used to estimate intrinsic value metrics from the Ohlson (1995) residual income valuation model.

3.3.1. Development of the Earnings Management Measure

The accounting literature has used three approaches to measure earnings management. These are: (i) the aggregate accrual approach (*e.g.,* Jones, 1991); (ii) the specific accrual approach (*e.g.*, McNichols and Wilson, 1988); and (iii) the distribution of earnings after manipulation approach (*e.g.*, Degeorge *et al.*, 1999). In the aggregate accrual approach, total accruals are regressed on selected nondiscretionary variables and the residual is taken as an estimate of discretionary accruals. This approach allows us to measure the magnitude of earnings management that arises from manipulation of all accrual accounts; however, the power of these aggregate models to find manipulation has been shown to be dismally low (*e.g.*, Bernard and Skinner, 1996). The specific accrual approach focuses on specific industry or contextual settings where one or more accruals tend to be sizable. It detects earnings management through a particular accrual account, rather than aggregating all manipulated accruals. The distribution of earnings after management approach focuses on the behaviour of earnings around a specified benchmark and tests whether the instances of amounts above and below the benchmark are distributed smoothly or whether it simply reflects discontinuities due to the exercise of discretion. This is a powerful tool for identifying contexts in which large numbers of firms appear to manage earnings. However, it is silent on the magnitude of manipulation at an individual firm-year/quarter level. Furthermore, it uses an imprecise benchmark (*i.e.*, whether earnings are slightly above earnings thresholds) to identify firms that manipulate earnings. In this study, I build on the aggregate accrual approach and the distribution of earnings after management approach to develop a measure of earnings management. I then validate the measure using both the total accrual approach the specific accrual approach. Specifically, to develop the measure I first use the aggregate accrual approach to compute discretionary accruals; I then use the distribution of earnings after management approach to identify firms that manipulate accruals to cross a specific earnings benchmark.

To facilitate the development and testing of the earnings management measure and ensure that I do not exhaust my entire sample in the process, as in Chapter 2, I first partition the sample into two sub-samples. These are the validation sample and the test sample. I then use the validation sample to develop and test my earnings management measure and the test sample to carry out my main analyses. In the next sub-section, I present the sample statistics; and in the subsequent sub-sections, I describe the procedure used to develop and test the earnings management measure.

3.3.1.1. Sample Statistics

The population consists of all U.S. firms that have data on Compustat for the time period from 1983 to 2006. First, I randomly select 20% of the total firms and use them as the validation sample to develop the earnings management measure. I then use the remaining 80% of the firms as the test sample to conduct the main analyses. I use firms instead of firm-years to create the test and validation sample because estimating the forward-looking modified Jones model on the validation sample requires firms to have lagged accruals. If I randomly select 20% of the firm-years as the validation sample, then many of the lagged firm-years will not be in the validation sample. The unavailability of the lagged accrual data in the validation sample will result in a substantial reduction in the sample size. Using firms, instead of firm-years, to create the test and validation sample avoids this problem. The number of firms, firm-years, industries, and industry-years in the test and validation samples are reported in Table 11. To determine whether the randomization process is successful (*i.e.*, whether the generated test and validation samples are similar), I compare the industry and year distributions in the test and validation samples and plot these distributions in Figure 2. As shown in the figure, the test and validation samples have similar industry and year distributions.

3.3.1.2. Estimation of Discretionary Accruals

Earlier studies, such as Matsumoto (2002) and Bartov *et al.* (2002), use the Modified Jones models to estimate discretionary accruals to examine the impacts of earnings management on MBE. Dechow *et al.* (2003) propose a so-called forward-looking modified Jones (FLMJ) model and demonstrate that this model outperforms the Jones and Modified Jones models in capturing discretionary accruals. In this section, I first implement the FLMJ model on the validation sample. I then compare the estimation of the FLMJ model with the estimations of other Jones-type models. The FLMJ model is specified as follows:

$$Accrual_{it} = \alpha + \beta_1((1+k)\Delta sales_{i,t} - \Delta AR_{i,t}) + \beta_2 GPPE_{i,t} + \beta_3 Accrual_{it-1} + \beta_4 Gr\_Sales_{it+1} + \varepsilon_{it} \qquad (3.1)$$

where $Accrual_{it}$ is firm *i*'s total accruals from year *t*,

$\Delta Sales_{it}$ is the change in firm *i*'s sales revenue (Compustat data item #12) from year *t-1* to *t*, ΔAR_{it} is the change in firm *i*'s accounts receivable from operating activities from year *t-1* to *t* (Compustat data item #302), $GPPE_{it}$ is firm *i*'s year *t* gross property plant and equipment – land excluded (Compustat data item #7); and GR_Sales_{it+1} is the change in firm *i*'s sales from year *t* to year *t+1*, and ε_{it} is zero-mean random error term.

Hribar and Collins (2002) show that the balance-sheet method may produce substantial errors in accrual estimation. Therefore, I use the cash-flow statement approach to calculate $Accrual_{it}$ by subtracting its operating cash flows from its net income:

$$A_{it} = EBEI_{it} - CFO_{it} \tag{3.2}$$

where $EBEI_{it}$ is firm *i*'s income before extraordinary items in year *t* (Compustat item #123), CFO_{it} is firm *i*'s cash flows from operations in year *t* (Compustat item #308).

The coefficient *k* in (3.1) is estimated from the regression

$$\Delta AR_{it} = a + k\Delta Sales_{it} + \zeta_{it} \tag{3.3}$$

by ordinary least squares (OLS), where the slope coefficient (*k*) in (3.3) represents the expected changes in account receivables for a given one-unit change in sales, and ζ_{it} is a zero-mean error term. I then use the OLS estimate of the slope coefficient to construct the unexpected portion of the change in account receivable due to the change in sales in (3.1) as $(1+k)\Delta Sales_{it} - \Delta AR_{it}$.

Setting $a = k = \beta_3 = \beta_4 = 0$ reduces (3.1) to the Modified Jones model proposed by Dechow *et al.* (1995), and if, in addition, $\Delta Sales_{it}$ is left unsubtracted from ΔAR_{it}, then I obtain the original Jones (1991) model. In other words, the FLMJ model includes three adjustments to the MJ model. First, rather than assuming all credit sales are discretionary, the model treats part of the increase in credit sales as expected by regressing ΔAR_{it} on $\Delta Sales_{it}$. Second, a portion of total accruals is assumed to be predictable and captured by including last year's accruals (i.e., lagged total accruals) in the model. Third, the Modified Jones model treats increases in inventory made in anticipation of higher sales as an abnormal accrual reflecting earnings manipulation rather than as a rational increase in inventory. Including future sales growth corrects for such misclassifications; however, it means that the FLMJ model uses future period data to estimate current period normal and abnormal accruals.

Table 12 summarizes the sample statistics for estimating the FLMJ model on the validation sample. The data used to estimate the model are obtained from the Compustat Industry Annual file. I use the cash flow statement approach to calculate accruals. The data required to compute accruals in the cash flow approach restrict the sample to a period from 1988 to 2006, because Compustat did not start to report these cash flow statement data until 1987 and the FLMJ model requires data on lagged accruals. As in Richardson *et al*. (1999), I exclude firms in financial and regulated industries (SIC code 4400-5000 and 6000-6999) because their accounting rules differ from those of firms in other industries. To estimate *k* for each industry-year, I delete industry-years that have fewer than 10 firm-year observations.

I compare the estimation of the FLMJ model in my study and Dechow *et al.* (2003) in Panel A of Table 13. The sample used in Dechow *et al.* (2003) spans from 1988 to 2000, whereas my study extends the sample period to 2006. The estimated *k* and estimate coefficients for the non-discretionary variables are similar to those reported in Dechow *et al.* (2003). The adjusted R-square is slightly higher in my study than in Dechow *et al.* (0.253 versus 0.200) as expected since I have a longer sample for estimation. Next, I compute discretionary accruals as the difference between total accrual and estimated non-discretionary accruals, $DA_{it} = A_{it} - NDA_{it}$, where NDA_{it} is calculated as the predicted values from the FLMJ regression in (3.1), To justify my choice of the FLMJ model over the other Jones-type models on statistical ground, I estimate other versions of the Jones-type models and compare the performance of the FLMJ model to the performances of the other models. Specifically, I first examine whether the estimated coefficients are consistent with the theoretical predictions in terms of expected signs. I then follow Dechow *et al.* (2003) to compare model performance using the values of the adjusted R-square. The rationale for this strategy is that, in the Jones-type models, we regress total accruals on variables representing non-discretionary accruals and use the predicted residual from the model as a measure for discretionary accruals; however, this predicted residual may capture some non-discretionary accruals that are omitted from the model. Therefore, by including more non-discretionary accrual variables in the model, we can improve the explanatory power of the model and, in the process, reduce the extent of the measurement error contained in the discretionary accrual proxy.

The alternative models I estimate include the modified Jones model, the lagged Modified Jones model, and the FLMJ model without the sales growth variable. These models are specified as follows:

Modified Jones Model:

$$Accrual_{it} = \alpha + \beta_1(\Delta sales_{i,t} - \Delta AR_{i,t}) + \beta_2 GPPE_{i,t} + \varepsilon_{i,t} \tag{3.4}$$

Lagged Modified Jones Model:

$$Accrual_{it} = \alpha + \beta_1(\Delta sales_{i,t} - \Delta AR_{i,t}) + \beta_2 GPPE_{i,t} + \beta_3 Accrual_{i,t-1} + \varepsilon_{i,t} \tag{3.5}$$

FLMJ model without growth in sales variable:

$$Accrual_{it} = \alpha + \beta_1((1+k)\Delta sales_{i,t} - \Delta AR_{i,t}) + \beta_2 GPPE_{i,t} + \beta_3 Accrual_{i,t-1} + \varepsilon_{i,t} \qquad (3.6)$$

The results, as shown in Panel B of Table 13, suggest that all of the models produce estimated coefficients with correct signs and have magnitudes similar to those reported in prior studies. Notably, the FLMJ model produces the highest value of the adjusted R-square (= 0.253) and the "FLMJ model without sales growth component" ranks second with an adjusted R-square value of 0.230.

As can be seen from (3.1), Dechow *et al.* (2003) add future sales growth to the Jones model in order to control for variation in normal accruals. The rationale for this inclusion is that firms anticipating sales growth will rationally increase inventory balances. However, there is a problem with using the actual sales changes in period *t+1* as a proxy for the expected growth. In particular, the objective of constructing an accrual model in my study is to examine the implications of earnings management for valuation. As Healy (1995) points out, the integration of any information that becomes known only in future periods would make the model useless for ex ante analysis and so, for timely valuation. So the use of variables with values that become known only in the future undermines the practical usefulness of the model. Therefore, in this study I choose to use the FLMJ model without the sales growth variable to estimate discretionary accruals.

Firms with unusual performance are expected to have extreme accruals (see Kothari, *et al.*, 2005). I follow the performance-matching methodology described in Kothari *et al.* (2005) to control for the impact of performance on estimated discretionary accruals. Specifically, I match each firm-year with another firm-year that is in the same industry and year and has the closest ROA to the firm-year in question. I then adjust the discretionary accrual for this firm-year by the discretionary accrual of the matched firm.

The performance-adjusted discretionary accrual estimates (referred to hereafter as DA) have a mean of -0.002 and a median of -0.001 across all firms and years.

3.3.1.3. Validation: Use of DA to Identify Extreme Earnings Manipulators

In this section, I validate the ability of performance-matched DA (or DA for short) to identify extreme earnings manipulators. Specifically, I examine whether DA can be used to identify firms that are targeted by SEC for earnings overstatement. To implement the test, I assign firm-years into DA deciles and examine the distribution of GAAP violators in the DA deciles. Firms create positive discretionary accruals to manage earnings up; therefore, if the discretionary accrual approach is capable of identifying extreme earnings manipulators, I would expect the SEC-GAAP violators to be concentrated in the top deciles of the DA distribution. Although prior studies, such as Dechow *et al.* (1995), also use GAAP violators to examine their discretionary accrual estimates, none of these studies use the same model (which is the FLMJ model omitting the future sales growth variable) as the one used in this study. Therefore, it is important to perform this validation in my study.

To construct the list of SEC GAAP violators, I combine the list of firms that were subjected to SEC enforcement actions for earnings overstatement for the period 1992-2001 from Erickson *et al.* (2004) and for the period 1994-2003 from Lane and O'Connell (2006). This results in 95 firms. I then use the online WRDS name search tool to identify the GVKEY for each GAAP violator. Out of these 95 firms, 76 firms and 191 firm-years have valid GVKEY values. Out of these 76 firms and 191 firm-years, 14 firms and 34 firm-years are in the validation sample.

In Table 14, I report the distribution of these 34 GAAP violators in the DA deciles. Contrary to my prior expectation, I find no evidence of a concentrated distribution of GAAP violators in the top DA deciles. This result suggests that the DA measure estimated from the performance-adjusted FLMJ model does not have enough power to identify extreme earnings manipulators (GAAP violators).

To measure earnings management more accurately, in the next step I focus on a particular type of earnings management for a particular purpose, which is accrual manipulation for the purpose of avoiding negative earnings. This aligns my research on earnings management with my research on expectations management, which also focuses on benchmark-beating behaviour. Accordingly, I narrow the research question to "examining the impact of loss-avoidance accrual management on firm valuation". Specifically, I examine how this type of earnings management impacts the abilities of accounting valuation models to predict firms' true intrinsic values.

In the next section, I use discretionary accrual estimates to identify firms that manipulate accruals to meet the positive earnings benchmark, following the "distribution of earnings after management approach". In the subsequent section, I present a validation test for the ability of the proposed measure to capture the notion of earnings management.

3.3.1.4. Definition of Earnings Manipulators and Non-manipulators

Prior studies, such as Matsumoto (2002), define earnings manipulators to be the firm-years with positive DA and non-manipulators to be those with negative DA. However, since some firms may have positive DA by chance instead of by earnings manipulation, defining firm-years with positive DA as manipulators may misclassify many firm-years.

To avoid this pitfall, I use DA together with the zero-earnings benchmark to identify firms that are likely to have manipulated earnings for the purpose of avoiding negative earnings. Firms are motivated to report positive earnings to avoid punishment by the stock market (see Skinner and Sloan, 1999), to maximize management's bonus compensation (see Healy, 1995) and to enhance reputations with stakeholders (see Bowen *et al.*, 1995; Burgstahler and Dichev, 1997). One approach they take to achieve the positive earnings benchmark is to create income-increasing discretionary accruals. Therefore, I define earnings manipulators to be the firm-years whose earnings before discretionary accruals are less than zero and whose earnings after discretionary accruals are greater than zero. Since these firms are likely to have created income-increasing discretionary accruals to avoid reporting negative earnings, I refer to them as loss-avoidance accrual manipulators. In this context, "earnings" are measured using earnings before extraordinary items and "discretionary accrual" is the performance-adjusted discretionary accrual estimated from the FLMJ model.

As a next step, I construct a matched non-manipulator control sample. To do so, I first create a group of firms-years that have earnings before and after discretionary accrual both greater than zero. Since these firms do not need to manipulate accruals in order to produce positive earnings, I refer to them as non-manipulators. Finally, to construct the matched non-manipulator control sample, I match each firm-year in the manipulator group with another firm-year in the non-manipulator group that is in the same industry and year and has the closest lagged total assets (a measure of firm size) to the firm-year in question. Note that I previously matched each firm-year with another firm-year based on industry, year and ROA to construct performance-adjusted discretionary accruals. The purpose of that match was to control for the impact of performance on the magnitude of DA at the firm-year level. I now perform another match to construct the control sample. The purpose of this particular match is to control for group differences in aspects other than accrual manipulation to ensure that the results we observe later are due to manipulation rather than to differences between the two groups in other aspects. These two matches are not redundant and are both necessary to adequately control for confounding factors and alternative explanations.

3.3.1.5. Validation of the Earnings Management Measure

To validate the ability of this measure to capture the notion of earnings management, I use the validation sample to examine whether the classified manipulators have higher deferred tax expense (DTE) and special items than the matched non-manipulators. Philips *et al.* (2002) propose to use the DTE to detect earnings management. The argument for this is that the DTE is a component of a firm's total income tax expense. As such, it reflects the tax effects of temporary differences between book income and taxable income that arise primarily from accruals for revenue and expense items that affect book income and taxable income in different periods. Managers typically have more discretion under GAAP than under U.S. tax rules. If managers manage earnings upwards, they are expected to use their discretion under the GAAP in ways that do not affect current taxable income. If this is the case, then their accounting choices will generate book-tax differences that increase the DTE.[3] This argument suggests that the DTE is expected to be higher for earnings manipulators than for non-manipulators. The classified manipulators are also expected to have higher special items because prior studies, such as Marquardt and Wiedman (2002), have found that firms manage earnings through special items to avoid reporting losses and earnings decreases. In Table 15, it is clear that manipulators have significantly higher DTE and special items than non-manipulators. These results provide evidence in support of my classification of accrual manipulators and non-manipulators.

3.3.2. Estimation of Intrinsic Value Metrics from Ohlson (1995)

As in the expectations management chapter, I use Ohlson's (1995) model as the valuation framework to estimate intrinsic value metrics. Specifically, I construct the intrinsic value metric for each firm-year observation at the earnings announcement date, using the announced earnings, the book value, and the consensus analyst forecast issued by IBES in the earnings announcement month. I obtain the stock price at the same time to construct the intrinsic value-to-price (V/P) ratio.

3.4. Empirical Analyses

In this section, I first construct the earnings management measure and intrinsic value metrics on the test sample. I then conduct two empirical analyses to examine the impacts

[3] DTE is measured by a firm's deferred tax expense (Compustat data item #50) in year *t*, scaled by total assets (Compustat data item #6) in year *t*-1. DTE is a variable in change form derived from changes in balance sheet accounts, and is unlikely to follow a random walk. If managers engage in earnings management to increase earnings but not taxable income then, regardless of how the target is defined, such earnings management generates book-tax differences that result in a higher DTE than would be observed in the absence of such activity. Thus, the level of DTE, not the change in DTE, is the appropriate variable (Philips *et al.*, 2002).

of loss-avoidance accrual manipulation on the ability of accounting valuation models to predict firm value.

3.4.1. Sample Statistics

3.4.1.1. Estimation of the Intrinsic Value Metrics in the Test Sample

In this section, I implement Ohlson's (1995) valuation model using the test sample to obtain an intrinsic value estimate for each firm-year in this sample. The sample statistics for the estimation process are presented in Panel A of Table 16. Specifically, I first exclude firms in the financial and regulated industries. I then match the sample to CRSP and IBES. This reduces the sample to 7,853 firms and 179,148 firm-years. Obtaining book value and earnings data reduces the sample to 7,419 firms and 76,419 firm-years. Requiring analyst one-year-ahead earnings forecast data further reduces the sample to 6,398 firms and 49,296 firm-years. I then estimate the intrinsic value metrics for each firm -year observation at the earnings announcement date. The estimation process is detailed in Section 3.3.2. The data requirement for intrinsic value metrics further reduces the sample to 5,845 firms and 37,701 firm-years.

3.4.1.2. Definition of Accrual Manipulators and Non-manipulators

I use the test sample to estimate the FLMJ model for each firm-year observation at the earnings announcement date. I report the sample selection process in Panel B of Table 16. As shown in the table, firms in the financial and regulated industries are eliminated. Obtaining necessary data to construct each variable in the FLMJ model reduces the sample to 8,481 firms and 60,704 firm-years. Estimating the *k* parameter in the FLMJ model requires at least 10 firm-year observations for each industry-year. Excluding industry-years with fewer than 10 firm-year observations further reduces the sample to 8,421 firms and 60,110 firm-years. Therefore, the sample with valid discretionary accrual estimates consists of 8,421 firms and 60,110 firm-years from 43 industries and 719 industry-years.

I then merge the sample of discretionary accruals with the sample of intrinsic value estimates by firm-year to create the final sample of loss-avoidance accrual manipulators and non-manipulators. As reported in Panel C of Table 16, there are more industries and industry-years in the intrinsic value sample than in the discretionary accrual sample. This is because I have deleted industries (industry years) with fewer than 10 firm-year observations from the discretionary accrual sample, but not from the intrinsic value sample; furthermore, there are more firms and firm-years in the discretionary accrual sample than in the intrinsic value sample. This is because the intrinsic value measure has a stricter data requirement (*i.e.*, lagged and twice lagged book values) than the discretionary accrual measure. Consequently, merging the discretionary accrual and intrinsic value samples significantly reduces the sample to 4,915 firms and 29,241 firm-years. I then construct the loss-avoidance accrual manipulator sample and non-manipulator sample in the process as detailed earlier. This results in 4,721firm-years in the manipulator sample and 4,721 matched firm-years in the non-manipulator sample. I use the combined manipulator and non-manipulator sample of 3,170 firms and 9,442 firm years in the first empirical analysis to examine and compare the price (P), intrinsic value estimates (V) and V/P ratios for the manipulators and non-manipulators. I use the 1,299 firms and 3,014 firm-years that report earnings in February as the sample in the returns analysis.

3.4.1.3. Statistics for the merged earnings manipulators and expectations manipulators sample

To provide insight into how the earnings manipulators and expectations manipulators relate to each other, in this section, I examine the statistics for the expectations management sample (firm-years with valid expectations management measures), the earnings management sample (firm-years with valid earnings management measures), and the joint sample (firm-years with both valid earnings management and valid expectations management measures). For each sample, I compute the percentages of manipulators and non-manipulators. Table 17 reports the yearly sample statistics. The last row of this table summarizes the statistics for the total sample across all years.

The expectations management sample consists of non-financial and non-regulated U.S. firms that have the necessary analyst forecast data to construct the expectations management measure. As shown in the last row of Table 17, across all years this sample includes 30,241firm-year observations, 27% of which are classified as expectations manipulators. The earnings management sample consists of non-financial and non-regulated U.S. firms that have required accounting data (*e.g.*, earnings, sales, account receivable, etc.) to construct the earnings management measure. This sample includes 60,110 firm-year observations, 16.0% of which are classified as earnings manipulators. I then merge these two samples to construct a sample with both earnings management and expectations management measures. There is a significant sample reduction by merging these two samples because as detailed in Section 3.4.1.2, these two samples have different data requirement; therefore, the overlap of these two samples are relative small. As shown in the last row of Table 17, the merged sample includes 20,101 firm-year observations. Out of these 20,101 observations, 5,176 (or 27%) are classified as expectations manipulators and 3,382 (or 17%) are classified as earnings manipulators. Out of the 5,176 expectations manipulators, 18% are classified as earnings manipulators. This is similar to the proportion of earnings manipulators in the overall sample (17% versus 18%, with a t-statistic of 0.44). Out of the 3,382 earnings manipulators, 28% are classified as expectations manipulators. Again, this is similar to the proportion of expectations manipulators in the overall sample (27% versus 28%, with a t-statistic of 0.76).

In summary, the results in this table suggest that firms are more likely to manipulate expectations than they are to manipulate earnings (27% versus 16%, with a t-statistic of 3.86). Earnings manipulators and firm-years in the overall sample have similar probabilities of being expectations manipulators (28% versus 27%, with a t-statistics of 0.76). Similarly, expectations manipulators and firm-years in the overall sample have similar probabilities of being earnings manipulators (18% versus 17%, with a t-statistics of 0.44).

3.4.2. Empirical Analyses

In this section, I examine the impact of loss-avoidance accrual manipulation on the usefulness of earnings in accounting valuation models. As detailed in Chapter 2, the assumption about the extent of market efficiency has important implications on the appropriate tests to use. Building on results from Chapter 2, I assume that the market is long-term efficient. Specifically, stocks can be mispriced in the short-run, but price will converge to the true intrinsic value over the course of a few months. Under this condition, good intrinsic value metrics should be able to identify short-term mispricing and predict future returns through V/P ratios; furthermore, if earnings management impairs the ability of valuation models to predict firm value, then I should observe that intrinsic value metrics estimated using manipulated earnings will have less ability to predict future returns.

In Section 3.4.2.1, I compare stock prices, intrinsic value estimates, and V/P ratios for the manipulators and non-manipulator to see if the market recognizes and discounts for earnings manipulation. In Section 3.4.2.2, I use the V/P ratio portfolio strategy returns analysis to further examine whether earnings management impairs the ability of accounting valuation models to predict firm value. Consistent with hypothesis 2, I expect the V/P ratio portfolio strategy for the manipulators to have less ability to predict future returns than the V/P ratio portfolio strategy for the non-manipulators.

3.4.2.1. V, P, and V/P Ratio Comparisons: Manipulators vs. Non-manipulators

In Table 18, I compare manipulators and non-manipulators with respect to stock price, intrinsic value estimate, and V/P ratio in the year of manipulation and the year prior to manipulation. Stock price (P) for the manipulators is lower than that for the non-manipulators (16.84 *vs.* 18.80), and this difference of -1.97 is statistically significant at the 1% level (with a sample t-statistic of -4.39); the estimated intrinsic value (V) for the manipulators is slightly higher than that for the non-manipulators (10.79 *vs.* 10.39) and this difference of 0.40 is statistically significant at the 7% level (with a t-statistic of *t* =

1.78). As a result, the V/P ratio for the manipulators is significantly higher than that for the non-manipulators (0.89 versus 0.74) and this difference of 0.14 is statistically significant at the 1% level (with t = 8.37). To ensure that these group differences are due to accrual manipulation rather than other firm-specific factors, I examine V, P, and the V/P ratio for the two groups in the year prior to earnings manipulation. The rationale for this exercise is that if the V/P differences are due to firm-specific characteristics other than earnings management, then this difference as observed in the manipulation year should persist in years other than the manipulation year. As shown in Table 18, the pattern observed in the manipulation year does not hold in the year prior to manipulation. Specifically, although the intrinsic value estimate for the manipulators in the prior year is higher than that for the non-manipulators (10.35 versus 9.72) as it is in the manipulation year; the stock price for the manipulators in the prior year is actually higher than that for the non-manipulators (16.41 versus 16.14) and this difference is not statistically significant (with t = 0.51). Furthermore, the difference in V/P ratios between manipulators and non-manipulators in the prior year is much smaller in magnitude (0.05) and is not statistically significant at a 5% level (with t = 1.64). This suggests that the significantly lower price, slightly higher intrinsic value estimate and significantly higher V/P ratio for the manipulators in the manipulation year is more likely to be due to accrual manipulation than to differences in other aspects between the two groups. Thus, it seems that the market does recognize and discount for accrual manipulation. However, it is unclear whether the price discount for the manipulators is appropriate and whether intrinsic value metrics estimated using manipulated earnings still represent good measures for firm value. To investigate this issue, I next examine and compare the abilities of the V/P ratio portfolio strategies for the manipulators and non-manipulators to predict future returns.

3.4.2.2. V/P ratio Portfolio Strategy Returns Test

The rationale for the returns test is that, assuming that the market is long-term efficient and that it takes a few months for price to converge to the true value, a good intrinsic value metric should be able to identify potential stock mispricing and predict future returns through V/P ratios. Furthermore, if loss-avoidance accrual manipulation impairs the ability of the accounting valuation model to predict firms' intrinsic values, and if it does not affect the ability of the stock market to predict firm values to the same extent, in the sense that the stock market can identify and discount for such manipulation appropriately, then the V/P ratio portfolio strategy, where V is estimated using manipulated earnings, is expected to have less ability to identify stock mispricing and predict future returns than the V/P ratio portfolio strategy, where V is estimated using non-manipulated earnings.

Frankel and Lee (1998) estimate the intrinsic value metrics using analyst forecast-based residual income valuation model and then examine the returns to the V/P ratio portfolio strategies over the 12-, 24-, and 36-months returns windows. They find significant positive returns from the V/P ratio strategies, especially over longer return windows. However, Beaver (2002), Kothari (2001), and Lo and Lys (2000) express the concern that high V/P firms may have higher risks and, therefore, the returns from the V/P ratio portfolio strategy may be caused by uncontrolled risks. To address the possibility that the difference in V/P ratio portfolio returns between the manipulator and non-manipulator groups are due to differences in risks between the two groups, I use the calendar-time approach Fama and French returns regression to control for risks and obtain risk-adjusted returns. I then compare these risk-adjusted returns between the two manipulation groups. Although Frankel and Lee (1998) generally find stronger returns performance over longer time periods, I use a 12-month return window, because my classification of manipulator and non-manipulator is an annual event. Therefore, the classification holds for 12 months only. At the end of the 12th month there will be reclassification and prior manipulators may be reclassified as non-manipulators and vice-versa.

To ensure that the sample firm-years are aligned in calendar time, I use the 1,299 firms and 3,014 firm-years that report earnings in February as my sample. I choose to use February, because compared to other months it has the most firms reporting. To implement the strategy, for each manipulation group in February of each year, I rank firms by V/P ratio and partition them into quintiles. I then obtain the monthly returns for each firm for the next 12 months. For each manipulation group, I compute the average monthly return for each V/P quintile ($Ret_{m,t}^{Qn}$). Specifically, $Ret_{m,t}^{Q5-M}$ represents the average monthly return to the top V/P quintile for the manipulator group in month *m* of year *t;* $Ret_{m,t}^{Q1-M}$ represents the average monthly return to the bottom V/P quintile for the manipulator group in month *m* of year *t;* $Ret_{m,t}^{Q5-N}$ represents the average monthly return to the top V/P quintile for the non-manipulator group in month *m* of year *t;* and $Ret_{m,t}^{Q1-N}$ represents the average monthly return to the bottom V/P quintile for the non-manipulator group in month *m* of year *t.*

I obtain the Fama and French risk factors and the momentum factor from the "Fama-French, Momentum, and Liquidity" dataset on the WRDS database. I then regress the monthly returns for the top and bottom V/P quintiles for each manipulation group on the risk factors as follows:

$$Ret_{m,t}^{Q5-M} = \alpha_{m,t}^{Q5-M} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q5-M} \quad (3.7)$$

$$Ret_{m,t}^{Q1-M} = \alpha_{m,t}^{Q1-M} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q1-M} \quad (3.8)$$

$$Ret_{m,t}^{Q5-N} = \alpha_{m,t}^{Q5-N} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q5-N} \quad (3.9)$$

$$Ret_{m,t}^{Q1-N} = \alpha_{m,t}^{Q1-N} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q1-N} \quad (3.10)$$

where $MktRF_{m,t}$ is the value weighted monthly return to the Center for Research in Security Prices universe less the return on a one-month treasury bill, $SMB_{m,t}$ is the return to small stocks less the return on big stocks, $HML_{m,t}$ is the return to high book-to-market equity stocks less the return on low book-to-market equity stocks, and $UMD_{m,t}$ is the return on high past return stocks (winners) minus the return on low past return stocks (losers).

I use the estimated intercepts $\tilde{\alpha}_{m,t}^{Q5-N}$ and $\tilde{\alpha}_{m,t}^{Q1-N}$ as the risk-adjusted monthly quintile returns to the top and bottom V/P quintiles for the non-manipulator group. I then compute the risk-adjusted V/P ratio hedged portfolio return as the difference in the risk-adjusted quintile returns to the top and bottom V/P quintiles ($\tilde{\alpha}_{m,t}^{Q5-N}$ - $\tilde{\alpha}_{m,t}^{Q1-N}$). The t-statistics on the hedged portfolio returns are computed using the means and standard deviations of the two quintile returns. I report these risk-adjusted quintile returns and hedged-portfolio returns in Table 19.

Results on the individual quintile returns show that, for the non-manipulator group, the top V/P quintile is able to earn a significant positive return of 0.009 (with t = 2.78), while the return to the bottom V/P quintile is 0.005 and is not statistically significant at a 5% level (with t = 1.34). The hedge portfolio return, which is the difference in the risk-adjusted returns between the top and bottom V/P quintiles, is 0.004, and this return is statistically significant at a 5% level (with t = 3.17). This provides evidence for the ability of the intrinsic value metrics for the non-manipulators to identify stock mispricing and predict future returns through V/P ratios. In contrast, for the manipulator group, both the top and bottom V/P quintiles are unable to earn abnormal returns after controlling for risks; that is, the abnormal returns of 0.004 and 0.003 are statistically insignificant at a 5% level (with t = 1.24 and t = 1.02 respectively). The difference in risk-adjusted returns between the top and bottom V/P quintiles is quantitatively small (0.001) and statistically insignificant (with t = 0.74), providing evidence that for the manipulators, the V/P ratio portfolio strategy of buying firms in the top V/P quintile and selling firms in the bottom V/P quintile is not able to earn a significant return.

In summary, these returns results suggest that, in the absence of earnings management, the market is long-term efficient and intrinsic value metrics are good measures of firm value; consequently, intrinsic value metrics can identify short-term market mispricing and predict future returns through V/P ratios in the long-run when the market corrects its short-run mispricing. However, earnings management reduces the ability of intrinsic value metrics to identify stock mispricing and predict future returns through V/P ratios, but the market is efficient with respect to earnings management over the long-run–it identifies and appropriately discounts for such manipulation.

Consequently, V/P ratio portfolio strategies where V is estimated using manipulated earnings, have significantly lower returns than the V/P ratio portfolio strategy, where V is estimated using non-manipulated earnings. Overall, these results provide evidence in support of the joint hypothesis of [i] long-term market efficiency with respect to earnings management and [ii] the negative impact of earnings management on the usefulness of earnings in accounting valuation models.

3.5. Conclusion

In this chapter, I examine the impacts of earnings management on the ability of accounting valuation models to predict firm value. I first combine the aggregate accrual approach and the distribution of earnings after management approach to develop a measure that focuses on accrual manipulation to achieve positive earnings. I use this measure to identify firms that manipulate accruals to avoid reporting losses. I then create a matched sample of non-manipulators with earnings before and after discretionary accrual both greater than zero and matched to the manipulator group based on firm size, industry and year. I use the Ohlson (1995) model as a valuation framework to estimate intrinsic value metrics. I then examine how loss-avoidance accrual manipulation influences the performance of intrinsic value metrics to predict firm value.

My empirical results suggest that in the year prior to the earnings manipulation, stock price and V/P ratios are similar for accrual manipulators and non-manipulators. However, in the year of accrual manipulation, stock price become significantly lower and V/P ratio becomes significantly higher for the manipulators than for the non-manipulators. This suggests that the stock market does recognize and discount for earnings manipulation. To further investigate whether the price discount is appropriate and whether the intrinsic value metrics are still good measure for firm value in the presence of earnings management, I examine and compare the performances of the V/P ratio portfolio strategies for the manipulators and non-manipulators to predict future returns.

I use the calendar-time approach Fama and French returns regression to obtain risk-adjusted V/P quintile returns and then compute the V/P ratio portfolio returns for the manipulator group and non-manipulator group separately. I find that the returns to the V/P ratio portfolio strategy for the non-manipulator group are positive and statistically significant, providing evidence in favour of long-term market efficiency and the ability of intrinsic value metrics estimated using non-manipulated earnings to identify stock mispricing and predict future returns. However, the return to the V/P ratio portfolio strategy for the manipulator group is quantitatively small and statistically insignificant after controlling for risks. This suggests that the intrinsic value metrics estimated using manipulated earnings are no longer able to identify stock mispricing and predict future returns through V/P ratios. Overall, these results provide evidence in support of the joint hypothesis of [i] long-term market efficiency, and [ii] the negative impact of earnings management on the ability of accounting valuation models to predict firm value.

REFERENCE

Bartov, E., Givoly, D., and Hayn, C., 2002. The rewards to meeting or beating earnings expectations, *Journal of Accounting and Economics* 33, 173–204.

Beaver, W. H. 2002. Perspectives on recent capital market research. *The Accounting Review* 77, 453–474.

Begley, J. and Feltham, G.A., 2002. The relation between market values, earnings forecasts, and reported earnings, *Contemporary Accounting Research* 19:1, 1–48.

Bernard, V.L., 1995. The Feltham-Ohlson framework: Implications for empiricists, *Contemporary Accounting Researc*h 11:2, 733–747.

Bernard, V.L., and D. Skinner. 1996. What motivates managers' choice of discretionary accruals? *Journal of Accounting and Economics 22* (1-3):313-325.

Bernhardt, D. and Campello, D., 2007. The dynamics of earnings forecast management, *Review of Finance* 11, 287-324.

Bowen, R. M., L. DuCharme, and D. Shores. 1995. Stakeholders' implicit claims and accounting method choice. *Journal of Accounting and Economics* 20: 255-295.

Brown, L.D., Hagerman, R.L., Griffin, P.A. and Zmijewski, M.E., 1987. Security analyst superiority relative to univariate time-series models in forecasting quarterly earnings, *Journal of Accounting & Economics* 9, 61–87.

Brown, L.D., and Pinello, A.S. 2007. To what extent does the financial reporting process curb earnings surprise games? *Journal of Accounting Research,* Vol. 45, Issue 5. Pp. 947-981.

Burgstahler, D.C., and Dichev, I., 1997. Earnings management to avoid earnings decreases and losses, *Journal of Accounting and Economics* 24, 99–126.

Cheng, Q., 2005. The Role of analysts' forecasts in accounting-based valuation: A critical evaluation, *Review of Accounting Studies* 10 (1), 5-31.

Collins, D. W. and P.S. Hribar, 2002. "Errors in estimating accruals: implications for empirical research." *Journal of Accounting Research 40.* 105-134.

Cotter, J., Tuna, I., and Wysocki, P., 2006. Expectations management and beatable targets: How do analysts react to public earnings guidance?. *Contemporary Accounting Research*, Vol. 23, No. 3.

Das, S., Levine, C. and Sivaramakrishnan, K., 1998. Earnings predictability and bias in analysts' earnings forecasts, *The Accounting Review* 73, 277–294.

Dechow, P., Sloan, R., and Sweeney, A., 1995. Detecting earnings management, *The Accounting Review* 70:2, 193–225.

Dechow, P.M., Hutton, A.P. and Sloan, R.G., 1999. An empirical assessment of the residual income valuation model, *Journal of Accounting & Economics* 26, 1–34.

Dechow, P. M., Richardson, S. A., and Tuna, I., 2003. Why are earnings kinky? An examination of the earnings management explanation, *Review of Accounting Studies* 8, 355–384.

Degeorge, F., Patel, J., Zeckhauser, R., 1999. Earnings management to exceed thresholds. Journal of Business 72 (1), 1–33.

Erickson, M., and S-w. Wang. 1999. Earnings management by acquiring firms in stock for stock mergers. *Journal of Accounting and Economics* 17 (January): 145-176.

Erickson, M., M. Hanlon, and E. Maydew. 2004. Is there a link between executive compensation and accounting fraud? Working paper.

Feltham, G.A. and Ohlson, J.A., 1995. Valuation and clean surplus accounting for operating and financial activities, *Contemporary Accounting Research* 11, 689–732.

Frankel, R. and Lee, C.M.C., 1998. Accounting valuation, market expectation, and cross-sectional stock returns, *Journal of Accounting and Economics* 25, 283–319.

Graham, J.R., Kumar, A., 2005. Do dividend clienteles exist? Evidence on dividend preferences of retail investors, Unpublished working paper. *Journal of Finance*, forthcoming.

Hand, J.R., 2001. Discussion of “Earnings, book values, and dividends in equity valuation: An empirical perspective”, *Contemporary Accounting Research* 18(1), 121–130.

Healy, P. 1985. The effect of bonus schemes on accounting decisions. *Journal of Accounting and Economics* 7: 85-107.

Healy, P. M., and J. M. Wahlen. 1999. A review of the earnings management literature and its implications for standard setting. *Accounting Horizons* 13: 365–383.

Jones, J. 1991. Earnings management during import relief investigations, *Journal of Accounting Research* 29, 193–228.

Kasznik, R., and Lev, B., 1995. To warn or not to warn: management disclosures in the face of an earnings surprise. *The Accounting Review*, Vol. 70, No. 1, pp. 113-134.

Kasznik, R., and McNichols, M., 2002. Does meeting earnings expectations matter? Evidence from analyst forecasts revisions and share prices, *Journal of Accounting Research* 40, 727–759.

Kothari, S. P. 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31, 105–232.

Kothari, S.P., A.J. Leone, and E.E. Wasley. 2005. *Journal of Accounting and Economics,* 39 (1), pp. 163-197.

Lane, R. and B.T. O'Connell., 2006. The changing face of the US SEC's Enforecement Investigations (AAERs) into Financial statement fraud in the post-Enron environment. Working Paper. James Cook University.

Lee, C.M.C., Myers, J. and Swaminathan, B., 1999. What is the intrinsic value of the Dow?, *The Journal of Finance* 54(5), 1693–1741.

Lo, K., and T. Lys. 2000. The Ohlson model: Contribution to valuation theory, limitations and empirical applications. *Journal of Accounting, Auditing and Finance* 15, 337–367.

Marquardt, C., and C. I. Wiedman, 2004. How are earnings managed? An examination of specific accruals. *Contemporary Accounting Research*, 21 (2), 461-491.

Matsumoto, D., 2002. Management's incentive to avoid negative earnings surprises, *The Accounting Review* 77, 483–514.

Matsunaga S. and C. Park, 2001. The effect of missing a quarterly earnings benchmark on the CEO's annual bonus, *The Accounting Review* **76** (2001), pp. 313–332.

McCrae, M. and H. Nilsson, 2001. The Explanatory and Predictive Power of Different Specifications of the Ohlson (1995) Valuation Models, *European Accounting Review*, Vol. 10, No. 2, pp. 314–41.

McNichols, M. and Wilson, P., 1988. Evidence of Earnings Management from the Provision for Bad Debts. *Journal of Accounting Research*, Vol. 26, Studies on Management's Ability and Incentives to Affect the Timing and Magnitude of Accounting Accruals, pp. 1-31.

O'Brien, P.C., 1988. Analysts' forecasts as earnings expectations, *Journal of Accounting & Economics* 10, 53–83.

Ohlson, J.A., 1995. Earnings, book values, and dividends in equity valuation, *Contemporary Accounting Research* 11, 661–687.

Phillips, J.D., Pincus, M.P. and Rego, S.O., 2003. Earnings Management: New Evidence Based On Deferred Tax Expense. *The Accounting Review* Vol. 78. No. 2: 491-521.

Richardson, S., Teoh, S., Wysocki, P., 1999. Tracking analysts' forecasts over the annual earnings horizon: Are analysts' forecasts optimistic or pessimistic?, *Working Paper, University of Michigan.*

Skinner, D.J., and Sloan, R. G., 2002. Earnings surprises, growth expectations, and stock returns: Don't let an earnings torpedo sink your portfolio, *Review of Accounting Studies* 7, 289–312.

Teoh, S.H., I. Welch, and T.J. Wong. 1998. Earnings management and the post-issue performance of seasoned equity offerings. *Journal of Financial Economics* (October) 50: 63-99.

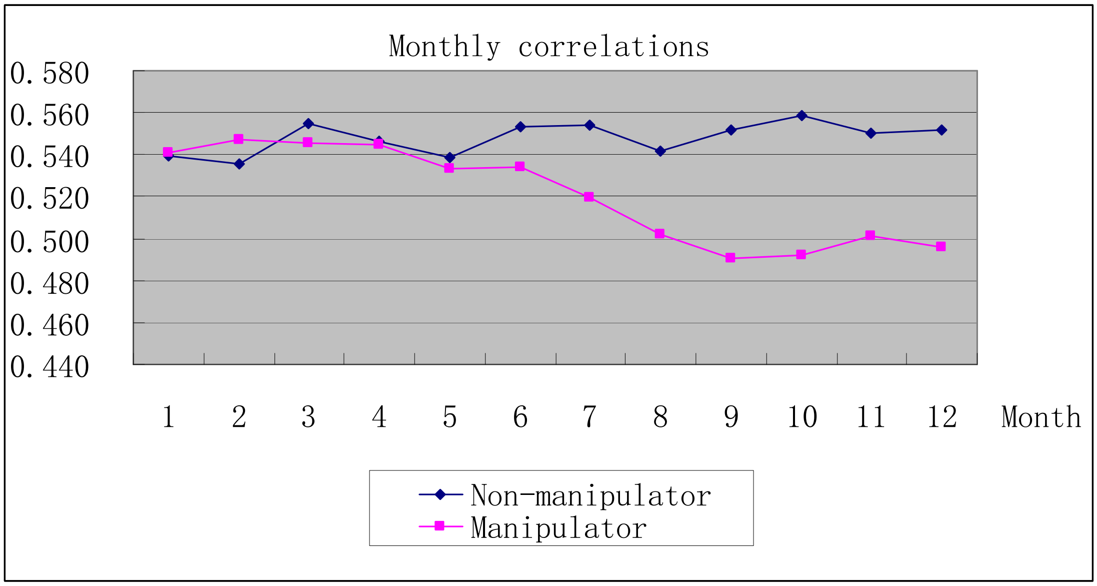
Vickers, M. 1999. Oh-hum, another earnings surprise. *Business Week* (May 24): 83-84.

Figure 1: Monthly Cross-Sectional Sample Correlations between Price and Intrinsic Value Estimates – Manipulators vs. Non-manipulators

For each manipulation group in each year *t*, I compute monthly sample correlations between price and intrinsic value estimate at the end of each month *m*. Intrinsic value metrics are estimated using two alternative risk premiums: 3% and 8%. Panel A of this table reports and plots the monthly sample correlations between price and intrinsic value estimate, where the intrinsic value is estimated using 3% risk premium, and Panel B plots the monthly correlations between price and intrinsic value estimate, where the intrinsic value is estimated using 8% risk premium.

Panel A: Monthly Sample Correlations between V and P, where V is Estimated using 3% Risk Premium

Correlation	**Mon1**	**Mon2**	**Mon3**	**Mon4**	**Mon5**	**Mon6**	**Mon7**	**Mon8**	**Mon9**	**Mon10**	**Mon11**	**Mon12**
non-manipulator	**0.539**	0.535	0.555	0.546	0.539	0.553	0.554	0.542	0.552	0.559	0.550	**0.552**
manipulator	**0.541**	0.547	0.546	0.545	0.533	0.534	0.519	0.502	0.491	0.492	0.501	**0.496**



Panel B: Monthly Sample Correlations between V and P, where V is Estimated using 8% Risk Premium

Correlation	**Mon1**	**Mon2**	**Mon3**	**Mon4**	**Mon5**	**Mon6**	**Mon7**	**Mon8**	**Mon9**	**Mon10**	**Mon11**	**Mon12**
non-manipulator	**0.538**	0.536	0.555	0.545	0.537	0.553	0.554	0.543	0.553	0.559	0.551	**0.552**
manipulator	**0.538**	0.542	0.543	0.542	0.529	0.532	0.517	0.500	0.489	0.491	0.501	**0.496**

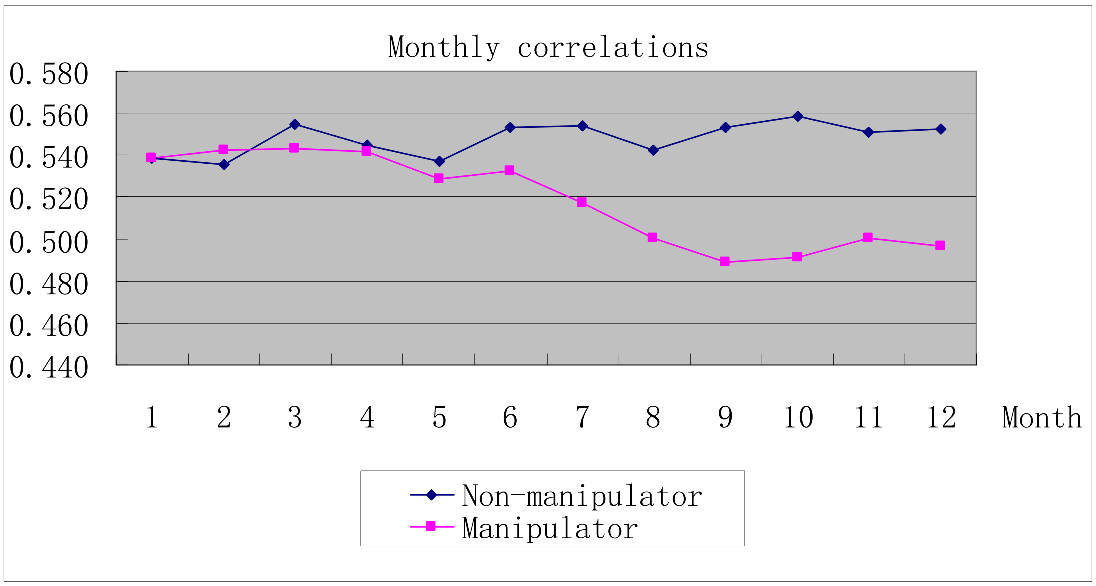
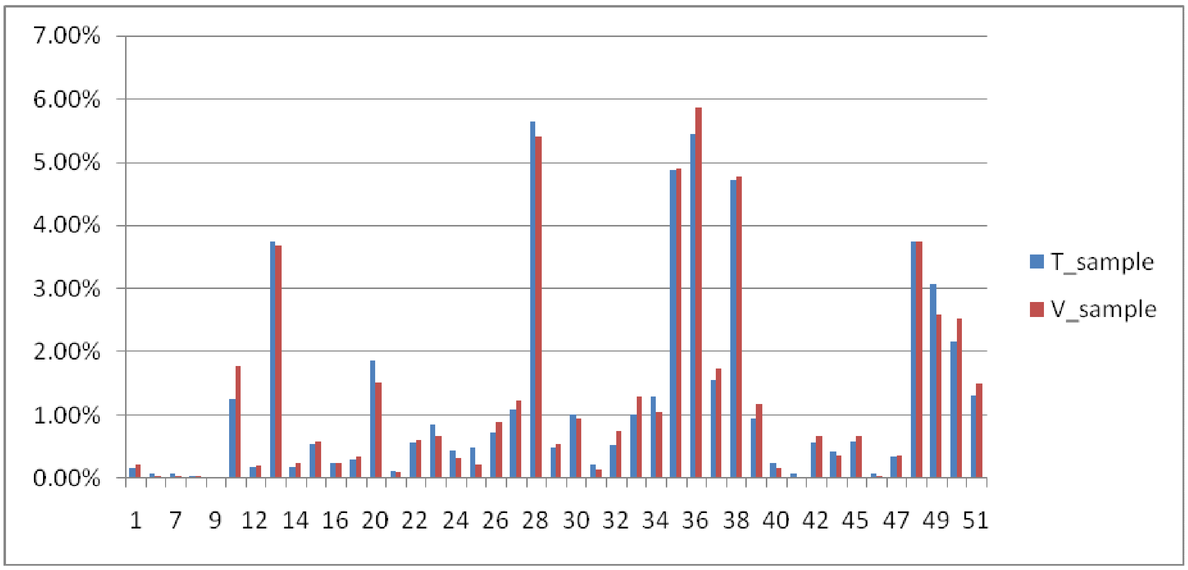


Figure 2: Industry and Fiscal Year Distributions in the Earnings Management Test and Validation Sample

The total sample consists of all U.S. firms that have data on Compustat for the time period from 1983 to 2006. The validation sample is constructed by randomly selecting 20% of the firms from the total sample, and the test sample consists of the remaining 80% of the firms in the total sample. Panel A of this figure plots the industry distribution of the test and validation sample and Panel B reports the year distribution in the test and validation sample.

Panel A: Industry distribution –Test vs. Validation Samples



Panel B: Year distribution –Test vs. Validation Samples

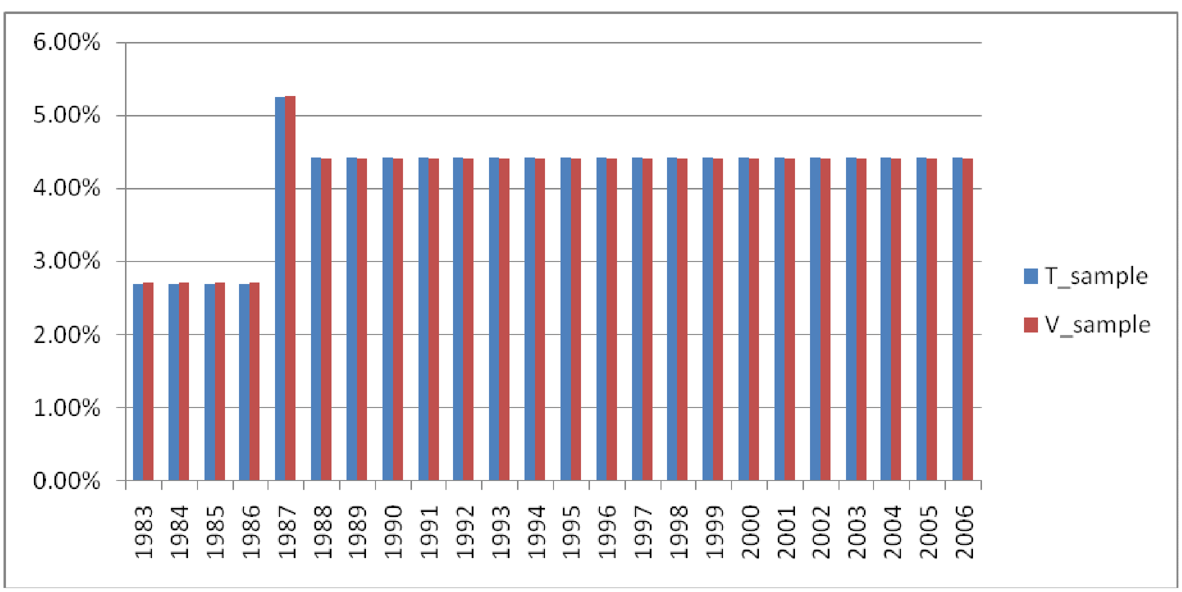


Table 1: Expectations Management - Sample Selection and Statistics
The sample consists of non-financial and non-regulated U.S. firms for the time period from 1988 to 2005. Analyst forecasts and the corresponding actual EPS data are obtained from IBES History U.S. Edition tape (*Actual File*) through WRDS. Stock price data are obtained from CRSP and accounting data are obtained from Compustat databases through WRDS.

	# of firms	**# of firm-years**
Construct expectation management measure		
Obtain forecast and actual EPS from IBES	14,335	88,600
Match to CRSP to obtain permco and SIC code	11,414	71,497
Match to Compustat to obtain gvkey	10,707	67,669
Delete firms in regulated and financial industries	6,992	46,043
Firm-years with valid measure for early consensus	6,336	38,173
Firm-years with valid measure for late consensus	6,397	35,643
Firm-years with both valid early and late consensus	5,575	30,319
Obtain returns data to estimate $Rev_{it} = b_0 + b_1 CRET_{it} + v_{it}$ to compute adjusted revision	5,570	30,303
Eliminate firms without lagged abnormal earnings	5,535	30,223
Create validation sample (20% of total firm-years)	3,145	6,044
Create test sample (the remaining 80% firm-years)	**5,272**	**24,179**
Construct intrinsic value measure (using the test sample)		
Obtain book value and number of shares outstanding	5,114	23,212
Obtain price data	5,112	23,208
Require firm-years to have lagged book value (b_{it-1})	5,062	23,046
Require firm-years to have twice lagged book value (needed to compute lagged abnormal earnings x^a_{it-1})	4,834	22,190
Sample for cross-sectional analysis	**4,834**	**22,190**
Require firm-years to have bi-monthly analyst forecasts	3,436	13,792
Sample for time-series analysis and returns analysis	**3,436**	**13,792**

Table 2: Validation Check: Expectations Management Measure

This table reports the results of validating the expectations management measure. Observations are 644 firm-years in the validation sample with management forecast data in the First Call's CIG dataset. Panel A of the table compares the classification of manipulators and non-manipulators in the proposed approach and the other two existing approaches. Panel B of the table reports the performances of the alternative classification approaches to detect management forecast guidance.

Panel A: Classification of Expectations Manipulators and Non-manipulators

Approach	**Classification**		
	Manipulators	Non-manipulators	Total firm-years
Tian	161 (25%)	483 (75%)	644
Bartov *et al.*	180 (28%)	464 (72%)	644
Matsumoto	266 (41%)	378 (59%)	644

Panel B: Performances of the Three Alternative Approaches to Capture Direct Evidence of Management Forecast Guidance

Approach	**Tian**			**Bartov *et al.***			**Matsumoto**		
Direction of guidance	Down	up/ neutral	Total	Down	up/ neutral	total	down	up/ neutral	total
Non-Manipulator	98	385	483	95	369	464	68	310	378
	20%	80%		20%	80%		18%	82%	
Manipulator	75	86	161	78	102	180	105	161	266
	47%	53%		43%	57%		39%	61%	
Total	173	471	644	173	471	644	173	471	644
Difference $\frac{M\%-N\%}{N\%}$	**130%**	**-33%**	Chi-square = 42.5	**112%**	**-29%**	Chi-square = 34.5	**119%**	**-26%**	Chi-square = 36.7

Table 3: Expectations management: Cross-sectional Sample Correlations between Stock Prices and Intrinsic Value Estimates

This table reports, for each manipulation group, the annual cross-sectional sample correlations between prices and intrinsic value metrics at the beginning and end of the year and the change in sample correlations from the beginning to the end of the year. Also reported is the difference in sample correlation changes between the manipulator and non-manipulator groups. The last row of the table, labelled "All years", reports the time-series sample means of the annual statistics across all years. The *t*-statistics are based on the time-series standard errors of the annual statistics. Intrinsic value metrics are estimated using two alternative risk premium of 3% and 8%. Panel A reports results for intrinsic value metrics estimated using 3% risk premium and Panel B reports results for intrinsic value metrics estimated using 8% risk premium.

Panel A: Sample Correlation Statistics for Price and Intrinsic Value Metrics Estimated using 3% Risk Premium.

	Manipulator (*M*)			**Non-manipulator (*N*)**			***M vs. N***		
Fiscal Year	**Corr_ Early**	**Corr_ Late**	**Corr_ Change**	**Corr_ Early**	**Corr_ Late**	**Corr_ Change**	**Corr_ Early**	**Corr_ Late**	**Corr_ Change**
1988	0.69	0.75	**0.07**	0.63	0.68	**0.05**	**0.06**	**0.07**	**0.02**
1989	0.74	0.61	**-0.14**	0.67	0.64	**-0.03**	**0.08**	**-0.03**	**-0.11**
1990	0.50	0.43	**-0.07**	0.63	0.59	**-0.05**	**-0.14**	**-0.16**	**-0.02**
1991	0.43	0.42	**-0.01**	0.58	0.58	**0.00**	**-0.14**	**-0.15**	**-0.01**
1992	0.70	0.65	**-0.05**	0.64	0.65	**0.01**	**0.06**	**0.01**	**-0.06**
1993	0.64	0.57	**-0.07**	0.65	0.61	**-0.04**	**-0.01**	**-0.04**	**-0.03**
1994	0.57	0.59	**0.02**	0.64	0.64	**-0.01**	**-0.07**	**-0.05**	**0.03**
1995	0.49	0.37	**-0.13**	0.64	0.60	**-0.04**	**-0.15**	**-0.24**	**-0.09**
1996	0.57	0.64	**0.07**	0.53	0.55	**0.02**	**0.04**	**0.09**	**0.05**
1997	0.65	0.56	**-0.09**	0.60	0.57	**-0.03**	**0.05**	**-0.01**	**-0.06**
1998	0.58	0.24	**-0.34**	0.53	0.42	**-0.10**	**0.06**	**-0.18**	**-0.24**
1999	0.19	-0.08	**-0.27**	0.39	0.27	**-0.12**	**-0.20**	**-0.34**	**-0.15**
2000	0.28	0.22	**-0.06**	0.20	0.30	**0.10**	**0.08**	**-0.08**	**-0.16**
2001	0.36	0.50	**0.15**	0.34	0.47	**0.12**	**0.02**	**0.04**	**0.03**
2002	0.56	0.54	**-0.02**	0.56	0.53	**-0.04**	**0.00**	**0.01**	**0.02**
2003	0.62	0.53	**-0.08**	0.52	0.58	**0.05**	**0.09**	**-0.04**	**-0.13**
2004	0.65	0.65	**0.00**	0.61	0.66	**0.05**	**0.04**	**0.00**	**-0.05**
2005	0.65	0.66	**0.01**	0.68	0.71	**0.02**	**-0.04**	**-0.05**	**-0.01**
All years	**0.55**	**0.49**	**-0.06 (t=-2.04)**	**0.56**	**0.56**	**0.00 (t=0.00)**	**-0.01 (t=0.53)**	**-0.06 (t=-2.44)**	**-0.06 (t=-3.07)**

Panel B: Sample Correlation Statistics for Price and Intrinsic Value Metrics Estimated using 8% Risk Premium.

	Manipulator (*M*)			**Non-manipulator (*N*)**			***M vs. N***		
Fiscal Year	**Corr_ Early**	**Corr_ Late**	**Corr_ Change**	**Corr_ Early**	**Corr_ Late**	**Corr_ Change**	**Corr_ Early**	**Corr_ Late**	**Corr_ Change**
1988	0.68	0.75	0.07	0.64	0.68	0.04	0.04	0.11	0.03
1989	0.75	0.61	-0.13	0.66	0.64	-0.02	0.09	-0.05	-0.11
1990	0.50	0.41	-0.08	0.63	0.58	-0.05	-0.14	-0.20	-0.03
1991	0.43	0.42	-0.01	0.57	0.57	0.00	-0.14	-0.15	-0.01
1992	0.72	0.66	-0.05	0.64	0.65	0.01	0.08	0.01	-0.06
1993	0.64	0.57	-0.07	0.65	0.61	-0.04	-0.01	-0.08	-0.03
1994	0.61	0.59	-0.01	0.64	0.64	0.00	-0.04	-0.05	-0.01
1995	0.49	0.37	-0.13	0.64	0.60	-0.04	-0.15	-0.27	-0.09
1996	0.57	0.65	0.07	0.53	0.55	0.02	0.04	0.11	0.05
1997	0.65	0.56	-0.09	0.60	0.57	-0.03	0.05	-0.04	-0.06
1998	0.59	0.25	-0.34	0.53	0.42	-0.10	0.06	-0.28	-0.24
1999	0.19	-0.07	-0.27	0.39	0.26	-0.13	-0.20	-0.47	-0.14
2000	0.28	0.22	-0.06	0.20	0.30	0.10	0.08	0.03	-0.16
2001	0.36	0.50	0.15	0.34	0.47	0.12	0.01	0.16	0.03
2002	0.56	0.54	-0.02	0.57	0.53	-0.04	0.00	-0.03	0.02
2003	0.62	0.53	-0.08	0.52	0.58	0.05	0.09	0.01	-0.14
2004	0.65	0.65	0.00	0.61	0.66	0.05	0.04	0.04	-0.04
2005	0.65	0.66	0.01	0.69	0.71	0.02	-0.04	-0.03	-0.01
All years	**0.55**	**0.49**	**-0.06 (t=-2.14)**	**0.56**	**0.56**	**0.00 (t=0.00)**	**-0.01 (t=-0.33)**	**-0.07 (t=-1.75)**	**-0.06 (t=-3.14)**

Table 4: Time-series Properties of V/P Ratios for the Manipulators and Non-manipulators

In each year, I compute bi-monthly V/P ratios for each manipulation group at the end of each two months. To examine the time-series properties of the bi-monthly V/P ratios throughout the year, I compute the sample standard deviations and the first-order autocorrelation coefficients of the bi-monthly aggregated V/P ratios for each manipulation group. I then take the means of these statistics across the 18 years (1988 to 2005) for each manipulation group and report these yearly and across-year average statistics for the two manipulation group in Panel A and B respectively. In Panel C of this table I report the difference in the standard deviations (Std Dev) and the first-order autoregressive coefficients (AR1) for the manipulators and non-manipulators in each year. The last row of Panel C summarizes the across-year differences in these statistics. The *t*-statistics are based on the time-series standard error from the annual statistics.

Panel A: Yearly V/P Ratio Statistics: Manipulator

Fiscal Year	V/P*2*	V/P*4*	V/P*6*	V/P*8*	V/P*10*	V/P*12*	Mean V/P (V/P*2*~V/P*12*)	Std Dev (V/P*2*~V/P*12*)	*AR1* (V/P*2*~V/P*12*)
1988	0.62	0.68	0.67	0.69	0.66	0.61	0.65	0.03	0.02
1989	0.60	0.63	0.58	0.57	0.55	0.55	0.58	0.03	0.45
1990	0.59	0.63	0.68	0.78	0.74	0.69	0.69	0.07	0.43
1991	0.51	0.52	0.50	0.49	0.48	0.41	0.49	0.04	0.31
1992	0.64	0.69	0.74	0.76	0.70	0.68	0.70	0.04	0.28
1993	0.56	0.54	0.54	0.52	0.51	0.48	0.52	0.03	0.27
1994	0.58	0.59	0.60	0.56	0.57	0.55	0.57	0.02	0.29
1995	0.47	0.45	0.42	0.42	0.41	0.40	0.43	0.03	0.47
1996	0.44	0.43	0.49	0.48	0.47	0.48	0.47	0.02	0.25
1997	0.46	0.43	0.42	0.42	0.44	0.44	0.43	0.02	0.12
1998	0.36	0.38	0.42	0.47	0.43	0.41	0.41	0.04	0.42
1999	0.28	0.29	0.28	0.28	0.23	0.19	0.26	0.04	0.44
2000	0.42	0.49	0.53	0.57	0.58	0.57	0.53	0.06	0.46
2001	0.39	0.39	0.43	0.50	0.46	0.46	0.44	0.04	0.39
2002	0.43	0.47	0.55	0.64	0.58	0.59	0.54	0.08	0.45
2003	0.50	0.46	0.45	0.43	0.40	0.38	0.44	0.05	0.42
2004	0.44	0.46	0.51	0.50	0.48	0.48	0.48	0.03	0.23
2005	0.39	0.39	0.41	0.41	0.40	0.40	0.40	0.01	0.05
All Years	**0.48**	**0.49**	**0.51**	**0.53**	**0.51**	**0.49**	**0.50**	**0.04**	**0.32**

Panel B: Yearly V/P Ratio Statistics: Non-manipulator

Fiscal Year	V/P*2*	V/P*4*	V/P*6*	V/P*8*	V/P*10*	V/P*12*	Mean V/P (V/P*2*~V/P*12*)	Std Dev (V/P*2*~V/P*12*)	*AR1* (V/P*2*~V/P*12*)
1988	0.46	0.51	0.51	0.52	0.52	0.49	0.50	0.02	0.03
1989	0.52	0.53	0.50	0.50	0.50	0.49	0.51	0.01	0.21
1990	0.50	0.51	0.52	0.57	0.57	0.54	0.53	0.03	0.46
1991	0.50	0.51	0.50	0.51	0.50	0.48	0.50	0.01	0.07
1992	0.45	0.47	0.47	0.49	0.47	0.46	0.47	0.01	0.05
1993	0.43	0.42	0.42	0.42	0.41	0.41	0.42	0.01	0.35
1994	0.42	0.43	0.42	0.42	0.44	0.43	0.43	0.01	0.05
1995	0.43	0.42	0.40	0.40	0.40	0.40	0.41	0.01	0.36
1996	0.36	0.35	0.37	0.36	0.36	0.35	0.36	0.01	0.32
1997	0.37	0.35	0.33	0.33	0.35	0.35	0.35	0.01	0.18
1998	0.31	0.32	0.34	0.38	0.36	0.35	0.34	0.02	0.43
1999	0.35	0.33	0.34	0.35	0.35	0.34	0.34	0.01	0.10
2000	0.24	0.25	0.25	0.26	0.29	0.29	0.26	0.02	0.50
2001	0.34	0.31	0.32	0.39	0.36	0.37	0.35	0.03	0.28
2002	0.36	0.37	0.42	0.45	0.43	0.45	0.41	0.04	0.42
2003	0.44	0.41	0.40	0.39	0.37	0.35	0.40	0.03	0.41
2004	0.36	0.37	0.38	0.37	0.36	0.35	0.36	0.01	0.37
2005	0.35	0.34	0.36	0.35	0.35	0.35	0.35	0.01	0.03
All Years	**0.40**	**0.40**	**0.40**	**0.41**	**0.41**	**0.40**	**0.41**	**0.02**	**0.26**

Panel C: Standard Deviations and First-order Autoregressive Coefficients – Manipulators vs. Non-manipulators

	Std Dev (V/P*2*~V/P*12*)			***AR1* (V/P*2*~V/P*12*)**		
Fiscal Year	**Manipulator (M)**	**Non-manipulator (N)**	**M-N**	**Manipulator (M)**	**Non-manipulator (N)**	**M-N**
1988	0.03	0.02	0.01	0.02	0.03	-0.01
1989	0.03	0.01	0.01	0.45	0.21	0.24
1990	0.07	0.03	0.04	0.43	0.46	-0.03
1991	0.04	0.01	0.03	0.31	0.07	0.24
1992	0.04	0.01	0.03	0.28	0.05	0.23
1993	0.03	0.01	0.02	0.27	0.35	-0.08
1994	0.02	0.01	0.01	0.29	0.05	0.24
1995	0.03	0.01	0.01	0.47	0.36	0.11
1996	0.02	0.01	0.01	0.25	0.32	-0.07
1997	0.02	0.01	0.00	0.12	0.18	-0.06
1998	0.04	0.02	0.02	0.42	0.43	-0.01
1999	0.04	0.01	0.03	0.44	0.1	0.34
2000	0.06	0.02	0.04	0.46	0.5	-0.04
2001	0.04	0.03	0.01	0.39	0.28	0.11
2002	0.08	0.04	0.04	0.45	0.42	0.03
2003	0.05	0.03	0.01	0.42	0.41	0.01
2004	0.03	0.01	0.01	0.23	0.37	-0.14
2005	0.01	0.01	0.00	0.05	0.03	0.02
All Years	0.04	0.02	**0.02 (t=6.58)**	0.32	0.26	**0.06 (t=2.34)**

Table 5: Returns Predictability Analysis

To ensure that the sample firm-years are aligned in calendar time, I use firms that report in February as the sample for the returns test. For each manipulation group in each year, observations are ranked and assigned to quintiles based on V/P ratios. Equally-weighted buy-hold stock returns are accumulated for each quintile portfolio for the 12 months subsequent to the classification of expectations manipulation. The hedge portfolio return is then calculated as the difference between the returns for the top and bottom quintiles. I report these yearly returns results and across-year average returns for the manipulator and non-manipulator groups in Panel A and B of this table respectively. The *t*-statistic is computed from the standard errors of the annual statistics. In Panel C, I report the differences in portfolio returns between the manipulator and non-manipulator groups. The *t*-statistic is computed from the standard errors of the annual statistics.

Panel A: Quintile and Hedged Portfolio Returns—Manipulators

Fiscal Year	***Ret_Q1***	***Ret_Q2***	***Ret_Q3***	***Ret_Q4***	***Ret_Q5***	**Portfolio Return (*Ret_Q5-Ret_Q1*)**
1989	0.35	0.18	0.05	-0.05	-0.21	-0.56
1990	0.15	-0.05	0.24	-0.16	-0.05	-0.21
1991	0.41	0.37	0.27	0.81	0.43	0.02
1992	0.10	0.40	-0.08	0.13	0.17	0.08
1993	0.10	0.12	0.41	0.24	0.01	-0.09
1994	-0.13	-0.06	-0.21	-0.19	-0.15	-0.02
1995	0.17	0.41	0.68	-0.22	0.03	-0.14
1996	0.13	0.11	0.31	0.20	0.27	0.14
1997	0.23	0.09	0.17	-0.12	-0.03	-0.26
1998	0.83	0.04	-0.27	0.03	0.00	-0.83
1999	0.31	-0.16	0.02	0.09	0.28	-0.03
2000	-0.18	-0.09	0.37	0.12	-0.11	0.07
2001	0.05	0.35	0.50	-0.05	0.13	0.08
2002	-0.03	-0.30	-0.09	-0.16	-0.29	-0.26
2003	0.57	0.51	0.60	1.02	1.17	0.60
2004	0.07	0.23	0.24	0.16	0.21	0.15
2005	0.09	0.18	0.12	0.10	0.13	0.04
All Years	**0.19**	**0.14**	**0.19**	**0.11**	**0.12**	**-0.07 (t=-0.50)**

Panel B: Quintile and Hedged Portfolio Returns—Non-manipulators

Fiscal Year	***Ret_Q1***	***Ret_Q2***	***Ret_Q3***	***Ret_Q4***	***Ret_Q5***	**Portfolio Return (*Ret_Q5-Ret_Q1*)**
1989	0.18	0.08	0.11	0.05	-0.05	-0.23
1990	0.10	0.15	-0.02	-0.01	0.03	-0.07
1991	0.27	0.29	0.46	0.38	0.51	0.24
1992	-0.18	0.20	0.23	0.06	0.31	0.49
1993	0.16	0.14	0.17	0.27	0.25	0.09
1994	-0.08	-0.07	-0.06	-0.02	0.03	0.11
1995	0.39	0.24	0.29	0.23	0.21	-0.18
1996	0.13	0.34	0.40	0.35	0.35	0.22
1997	0.07	0.23	0.10	0.05	0.16	0.09
1998	0.49	-0.02	-0.24	-0.09	-0.10	-0.59
1999	0.42	0.10	0.01	0.09	0.31	-0.12
2000	0.20	0.46	0.33	0.40	0.24	0.04
2001	-0.14	0.11	0.08	-0.07	0.27	0.42
2002	-0.25	-0.20	-0.14	-0.19	-0.05	0.20
2003	0.49	0.51	0.47	0.64	1.01	0.52
2004	-0.04	0.12	0.17	0.28	0.13	0.17
2005	0.12	0.40	0.25	0.25	0.21	0.09
All Years	**0.14**	**0.18**	**0.15**	**0.16**	**0.22**	**0.09 (t=1.38)**

Panel C: Hedged Portfolio Returns – Manipulator vs. Non-manipulator

Fiscal Year	Portfolio Return: M	Portfolio Return: N	Portfolio Return: M-N
1989	-0.56	-0.23	-0.79
1990	-0.21	-0.07	-0.14
1991	0.02	0.24	-0.22
1992	0.08	0.49	-0.41
1993	-0.09	0.09	-0.18
1994	-0.02	0.11	-0.13
1995	-0.14	-0.18	0.04
1996	0.14	0.22	-0.08
1997	-0.26	0.09	-0.35
1998	-0.83	-0.59	-0.24
1999	-0.03	-0.12	0.09
2000	0.07	0.04	0.03
2001	0.08	0.42	-0.34
2002	-0.26	0.20	-0.46
2003	0.60	0.52	0.08
2004	0.15	0.17	-0.02
2005	0.04	0.09	-0.05
All Years	**-0.07 (t=-0.50)**	**0.09 (t=1.38)**	**-0.16 (t=-3.98)**

Table 6: V/P Ratio Portfolio Strategy Abnormal Returns after Controlling for Fama and French Risk Factors

The sample consists of 1,478 firms and 4,307 firm-years that report earnings in February. I rank firms by V/P ratio and assign them into quintiles. I then compute average monthly quintile returns and regress the monthly returns of the top and bottom V/P quintiles on the three Fama and French risk factors and the momentum factor in the following regressions:

$$\mathrm{Ret}_{m,t}^{Q5\_M} = \alpha_{m,t}^{Q5\_M} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q5\_M}$$
$$\mathrm{Ret}_{m,t}^{Q1\_M} = \alpha_{m,t}^{Q1\_M} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q1\_M}$$
$$\mathrm{Ret}_{m,t}^{Q5\_N} = \alpha_{m,t}^{Q5\_N} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q5\_N}$$
$$\mathrm{Ret}_{m,t}^{Q1\_N} = \alpha_{m,t}^{Q1\_N} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q1\_N}$$

This table reports the estimated coefficients from the above Fama and French returns regressions.

	Non-manipulator (N)			**Manipulator (M)**		
Dep. Var.	**Ret_Q5**	**Ret_Q1**	**Ret (Q5-Q1)**	**Ret_Q5**	**Ret_Q1**	**Ret (Q5-Q1)**
Intercept	0.008 (t=2.66)	0.004 (t=1.69)	**0.004 (t=4.20)**	-0.003 (t=-0.65)	0.006 (t=1.27)	**- 0.009 (t=-5.41)**
mktrf	1.256 (t=15.03)	1.154 (t=17.61)	0.102 (t=3.86)	1.332 (t=11.13)	1.139 (t=9.63)	0.193 (t=4.58)
smb	0.741 (t=8.63)	0.535 (t=7.95)	0.206 (t=7.54)	0.834 (t=6.52)	0.837 (t=6.62)	-0.003 (t=-0.06)
hml	0.785 (t=7.28)	-0.352 (t=-4.16)	1.137 (t=33.17)	0.817 (t=5.17)	-0.400 (t=-2.57)	1.218 (t=21.94)
umd	-0.542 (t=-8.83)	-0.132 (t=-2.75)	-0.410 (t=-21.02)	-0.344 (t=-3.77)	0.208 (t=2.31)	-0.552 (t=-17.23)

Table 7: Classification of Repetitive Manipulators and Non-manipulators

A firm-year is defined to be repetitive manipulators (MM) if it is classified as manipulators in both the current year and the previous year. It is defined to be non-repetitive manipulator (MN) if it is classified as a manipulator in current year and non-manipulator in the previous year. This table reports the sample statistics of current year and previous year manipulators and non-manipulators.

		Current year		
		Manipulator	Non-manipulator	Total
Prior year	Manipulator	1,418 (21.9%) (28.9%) (Repetitive Manipulator)	3,487 (19.1%) (71.1%)	4,905 (100%) (19.9%)
	Non-manipulator	3,488 (53.9%) (23.6%) (Non-repetitive Manipulator)	11,278 (61.9%) (76.4%)	14,766 (100%) (59.8%)
	Non-classifiable (no lagged data)	1,565 (24.2%) (31.2%) (Non-identifiable)	3,455 (19.0%) (68.8%)	5,020 (100%) (20.3%)
	Total	6,471 (100%) (26.2%) (manipulator)	18,220 (100%) (73.8%)	24,691 (100%)

Table 8: Cross-sectional Analysis: Repetitive vs. Non-repetitive Manipulators

This table reports the yearly correlation statistics for the repetitive and non-repetitive manipulators. Repetitive manipulators (MM) are defined to be the firm-years that are classified as manipulators in both the current year and the prior year. Non-repetitive manipulators (MN) are defined as the firm-years that are classified as manipulators in current year and non-manipulator in the previous year.

	Repetitive Manipulator (*MM*)			**Non-repetitive manipulator (*MN*)**			***MM vs. MN***		
Fiscal Year	**Corr_ Early**	**Corr_ Late**	**Corr_ Change**	**Corr_ Early**	**Corr_ Late**	**Corr_ Change**	**Corr_ Early**	**Corr_ Late**	**Corr_ Change**
1989	0.78	0.69	0.09	0.74	0.57	0.17	0.04	0.12	-0.08
1990	0.58	0.66	-0.08	0.51	0.37	0.14	0.07	0.29	-0.22
1991	0.34	0.30	0.04	0.45	0.46	-0.01	-0.11	-0.16	0.05
1992	0.61	0.45	0.16	0.77	0.76	0.01	-0.16	-0.31	0.15
1993	0.55	0.54	0.01	0.69	0.64	0.05	-0.13	-0.10	-0.04
1994	0.65	0.63	0.03	0.63	0.61	0.02	0.02	0.01	0.01
1995	0.52	0.32	0.20	0.46	0.35	0.11	0.05	-0.03	0.09
1996	0.49	0.55	-0.06	0.63	0.70	-0.07	-0.14	-0.15	0.01
1997	0.75	0.66	0.10	0.61	0.57	0.04	0.14	0.08	0.06
1998	0.45	0.11	0.34	0.61	0.35	0.26	-0.16	-0.25	0.09
1999	0.07	-0.10	0.17	0.29	-0.10	0.39	-0.22	0.00	-0.23
2000	0.29	0.37	-0.08	0.33	0.31	0.02	-0.04	0.06	-0.10
2001	0.44	0.47	-0.03	0.36	0.48	-0.12	0.08	-0.02	0.10
2002	0.57	0.69	-0.12	0.56	0.49	0.07	0.00	0.20	-0.19
2003	0.69	0.57	0.12	0.61	0.61	0.00	0.08	-0.04	0.12
2004	0.69	0.66	0.03	0.59	0.66	-0.07	0.10	0.00	0.10
2005	0.59	0.44	0.16	0.65	0.70	-0.04	-0.06	-0.26	0.20
All years	0.53	0.47	0.06 (t=2.13)	0.56	0.50	0.06 (t=1.82)	-0.03 (t=-0.23)	-0.03 (t=-0.17)	0.01 (t=0.19)

Table 9: Time-series Analysis: Repetitive vs. Non-repetitive Manipulators

Repetitive manipulators (MM) are as the firm-years that are classified as manipulators in both the current year and the previous year. Non-repetitive manipulators (MN) are defined as the firm-years that are classified as manipulators in current year and non-manipulator in the previous year. This table reports the V/P ratios, the standard deviation and the first-order autocorrelation coefficients (AR1) of the bi-monthly aggregated V/P ratios for MM and MN. Panel A and B report the yearly statistics for repetitive manipulators and non-repetitive manipulators respectively. I then take the mean of these bi-monthly V/P ratios and their standard deviations and autocorrelation coefficients in the *AR1* processes across the 18 years (1988 to 2005) for each manipulation group and report these summary statistics in the last row of each panel. In Panel C of this table, I report the difference in standard deviation and AR1s for the manipulators and non-manipulators. The *t*-statistics are based on the time-series standard error of the annual statistics.

Panel A: V/P Ratio Statistics for the Repetitive Manipulator (MM)

Fiscal Year	V/P_2	V/P_4	V/P_6	V/P_8	V/P_{10}	V/P_{12}	Mean V/P (V/P_2~V/P_{12})	Std Dev (V/P_2~V/P_{12})	*AR1* (V/P_2~V/P_{12})
1989	0.65	0.69	0.63	0.60	0.58	0.60	0.62	0.04	0.51
1990	0.59	0.63	0.67	0.79	0.72	0.65	0.68	0.07	0.32
1991	0.66	0.68	0.69	0.67	0.64	0.54	0.65	0.06	0.25
1992	0.57	0.63	0.67	0.72	0.67	0.66	0.65	0.05	0.28
1993	0.60	0.57	0.58	0.57	0.56	0.51	0.57	0.03	0.13
1994	0.63	0.65	0.66	0.64	0.66	0.62	0.64	0.02	0.32
1995	0.63	0.61	0.58	0.58	0.58	0.57	0.59	0.02	0.30
1996	0.48	0.48	0.53	0.49	0.50	0.53	0.50	0.02	0.20
1997	0.59	0.58	0.52	0.55	0.56	0.55	0.56	0.02	0.08
1998	0.38	0.39	0.41	0.48	0.43	0.36	0.41	0.05	0.13
1999	0.26	0.30	0.31	0.29	0.25	0.22	0.27	0.03	0.38
2000	0.47	0.55	0.58	0.59	0.66	0.65	0.58	0.07	0.39
2001	0.52	0.51	0.53	0.62	0.55	0.56	0.55	0.04	0.02
2002	0.52	0.56	0.64	0.75	0.67	0.70	0.64	0.09	0.39
2003	0.62	0.59	0.59	0.56	0.52	0.49	0.56	0.05	0.43
2004	0.48	0.50	0.56	0.55	0.53	0.52	0.52	0.03	0.24
2005	0.41	0.39	0.45	0.44	0.41	0.39	0.42	0.02	0.07
All Years	**0.53**	**0.55**	**0.57**	**0.58**	**0.56**	**0.54**	**0.55**	**0.04**	**0.26**

Panel B: V/P Ratio Statistics for Non-repetitive Manipulator

Fiscal Year	V/P_2	V/P_4	V/P_6	V/P_8	V/P_{10}	V/P_{12}	Mean V/P (V/P_2~V/P_{12})	Std Dev (V/P_2~V/P_{12})	*AR1* (V/P_2~V/P_{12})
1989	0.49	0.49	0.46	0.46	0.46	0.46	0.47	0.01	0.41
1990	0.48	0.48	0.49	0.53	0.52	0.50	0.50	0.02	0.46
1991	0.48	0.49	0.48	0.49	0.49	0.45	0.48	0.01	0.07
1992	0.46	0.48	0.48	0.50	0.48	0.47	0.48	0.01	0.20
1993	0.42	0.41	0.41	0.41	0.41	0.40	0.41	0.01	0.38
1994	0.42	0.43	0.43	0.42	0.44	0.43	0.43	0.01	0.18
1995	0.42	0.40	0.39	0.39	0.39	0.38	0.40	0.01	0.29
1996	0.37	0.37	0.38	0.37	0.36	0.35	0.37	0.01	0.17
1997	0.36	0.34	0.33	0.33	0.35	0.34	0.34	0.01	0.12
1998	0.31	0.32	0.34	0.37	0.35	0.35	0.34	0.02	0.45
1999	0.34	0.32	0.33	0.35	0.34	0.34	0.34	0.01	0.29
2000	0.29	0.28	0.28	0.29	0.31	0.32	0.30	0.01	0.55
2001	0.30	0.28	0.30	0.36	0.33	0.33	0.32	0.03	0.28
2002	0.33	0.34	0.39	0.42	0.40	0.42	0.38	0.04	0.44
2003	0.43	0.40	0.39	0.38	0.36	0.35	0.39	0.03	0.41
2004	0.35	0.36	0.37	0.36	0.35	0.35	0.36	0.01	0.34
2005	0.33	0.32	0.35	0.34	0.34	0.34	0.34	0.01	0.12
All Years	**0.39**	**0.38**	**0.39**	**0.40**	**0.39**	**0.39**	**0.39**	**0.02**	**0.30**

Panel C: Standard Deviations and AR1s – Repetitive Manipulators vs. Non-repetitive Manipulators

	Std Dev (V/P_2~V/P_{12})			***AR1* (V/P_2~V/P_{12})**		
Fiscal Year	**MM**	**MN**	**MM-MN**	**MM**	**MN**	**MM-MN**
1989	0.04	0.01	0.03	0.51	0.41	0.1
1990	0.07	0.02	0.05	0.32	0.46	-0.14
1991	0.06	0.01	0.05	0.25	0.07	0.18
1992	0.05	0.01	0.04	0.28	0.2	0.08
1993	0.03	0.01	0.02	0.13	0.38	-0.25
1994	0.02	0.01	0.01	0.32	0.18	0.14
1995	0.02	0.01	0.01	0.3	0.29	0.01
1996	0.02	0.01	0.01	0.2	0.17	0.03
1997	0.02	0.01	0.01	0.08	0.12	-0.04
1998	0.05	0.02	0.03	0.13	0.45	-0.32
1999	0.03	0.01	0.02	0.38	0.29	0.09
2000	0.07	0.01	0.06	0.39	0.55	-0.16
2001	0.04	0.03	0.01	0.02	0.28	-0.26
2002	0.09	0.04	0.05	0.39	0.44	-0.05
2003	0.05	0.03	0.02	0.43	0.41	0.02
2004	0.03	0.01	0.02	0.24	0.34	-0.1
2005	0.02	0.01	0.01	0.07	0.12	-0.05
All Years	0.04	0.02	**0.02 (t=3.68)**	0.26	0.30	**-0.04 (t=-1.07)**

Table 10: Returns Analysis: Repetitive vs. Non-repetitive Manipulators

Repetitive manipulators (MM) are defined as the firm-years that are classified as manipulators in both the current year and the previous year. Non-repetitive manipulators (MN) are defined as the firm-years that are classified as manipulators in current year and non-manipulator in the previous year. For each manipulation group in each year, observations are ranked and assigned to quintiles based on V/P ratios. Equally-weighted buy-hold stock returns are accumulated for each quintile portfolio for the 12 months subsequent to the classification of expectations manipulation. The hedge portfolio return is then calculated as the difference between the returns for the top and bottom V/P quintiles. I report these yearly results for the manipulator and non-manipulator groups in Panel A and B of this table. I then take the means of these annual portfolio returns across the 18 sample years for each manipulation group and report the cross-year mean returns in the last row of these two Panels. In Panel C I report the differences in portfolio returns between the repetitive and non-repetitive manipulator groups. The *t*-statistic is computed from the standard errors of the annual statistics.

Panel A: Quintile and Hedged Portfolio Returns—Repetitive Manipulators

Fiscal Year	***Ret_Q1***	***Ret_Q2***	***Ret_Q3***	***Ret_Q4***	***Ret_Q5***	**Portfolio Return (*Ret_Q5-Ret_Q1*)**
1990	0.11	-0.34	0.31	-0.28	-0.03	-0.14
1991	0.49	0.19	0.89	0.06	0.31	-0.18
1992	1.14	0.19	-0.26	0.21	0.08	-1.06
1993	0.58	-0.20	0.40	0.41	-0.19	-0.77
1994	-0.39	0.03	-0.11	-0.22	-0.22	0.18
1995	0.53	0.48	-0.10	-0.07	-0.16	-0.70
1996	0.49	0.16	0.23	0.25	0.06	-0.43
1997	0.12	0.51	0.10	-0.07	0.33	0.21
1998	0.73	-0.17	-0.29	-0.41	0.23	-0.50
1999	-0.26	-0.11	-0.43	-0.28	0.32	0.59
2000	-0.53	0.44	0.00	-0.09	-0.40	0.13
2001	0.03	-0.10	0.12	0.60	0.89	0.86
2002	-0.17	-0.38	0.07	-0.18	-0.59	-0.42
2003	0.37	0.42	0.54	0.49	1.05	0.68
2004	0.11	0.66	0.27	0.29	0.44	0.33
2005	0.02	0.25	0.07	0.24	0.14	0.12
All Years	**0.21**	**0.13**	**0.11**	**0.06**	**0.14**	**-0.07**

Panel B: Quintile and Hedged Portfolio Returns—Non-repetitive Manipulators

Fiscal Year	***Ret_Q1***	***Ret_Q2***	***Ret_Q3***	***Ret_Q4***	***Ret_Q5***	**Portfolio Return (*Ret_Q5-Ret_Q1*)**
1990	0.10	0.10	0.07	0.05	0.04	-0.06
1991	0.00	0.13	-0.04	-0.02	0.10	0.10
1992	0.03	0.16	0.05	0.09	0.09	0.05
1993	0.04	0.08	0.10	-0.07	0.09	0.06
1994	0.13	0.15	0.06	0.08	0.03	-0.10
1995	0.15	0.10	-0.16	-0.11	0.18	0.03
1996	0.22	0.13	0.10	0.18	0.15	-0.07
1997	0.17	0.00	0.13	0.00	0.07	-0.11
1998	0.09	0.16	0.04	0.04	0.02	-0.07
1999	0.14	0.09	0.07	0.16	0.23	0.09
2000	-0.03	-0.02	0.05	0.02	0.30	0.33
2001	0.07	0.19	0.23	0.12	0.17	0.10
2002	0.21	0.12	0.26	0.31	0.26	0.05
2003	0.44	0.32	-0.04	0.92	0.31	-0.13
2004	0.21	0.48	0.22	0.32	0.13	-0.08
2005	-0.01	0.21	0.05	0.05	0.23	0.24
All Years	**0.12**	**0.15**	**0.07**	**0.13**	**0.15**	**0.03**

Panel C: Hedged Portfolio Returns – Repetitive vs. Non-repetitive Manipulators

Fiscal Year	Portfolio Return: MM	Portfolio Return: MN	Portfolio Return: MM-MN
1990	-0.14	-0.06	-0.08
1991	-0.18	0.10	-0.28
1992	-1.06	0.05	-1.11
1993	-0.77	0.06	-0.83
1994	0.18	-0.10	0.28
1995	-0.70	0.03	-0.73
1996	-0.43	-0.07	-0.36
1997	0.21	-0.11	0.32
1998	-0.50	-0.07	-0.43
1999	0.59	0.09	0.5
2000	0.13	0.33	-0.2
2001	0.86	0.10	0.76
2002	-0.42	0.05	-0.47
2003	0.68	-0.13	0.81
2004	0.33	-0.08	0.41
2005	0.12	0.24	-0.12
All Years	**-0.07**	**0.03**	**-0.10 (t=-0.68)**

Table 11: Earnings Management Sample Statistics – the Test and Validation Samples

The population consists of all U.S. firms with data on Compustat for the time period from 1983 to 2006. From this population, I randomly select 20% of the total firms and use them as the validation sample to develop and validate my earnings management measure. I then use the remaining 80% as the test sample to conduct the main analysis and examine the impact of earnings management on firm valuation. This table reports the number of industries, industry-years, firms and firm-years in the test and validation samples.

Number of observations	**Industries**	**Industry-years**	**Firms**	**Firm-years**
Validation sample	69	1,587	5,206	97,283
Test sample	74	1,693	20,823	391,626
Total sample	74	1,696	26,029	488,909

Table 12: Sample Statistics – Estimation of the FLMJ Model in the Validation Sample

This table reports the sample statistics (number of industries, industry-years and firm-years) at each step in estimating the FLMJ model in the validation sample.

Steps	**Industries**	**Industry-years**	**Firm-years**
Raw data (validation sample)	69	1,587	97,283
Sufficient data for each variable used in the FLMJ model to construct EM measure	69	1,136	20,038
Exclude financial and regulated industries	48	784	15,073
Exclude industry-years with less than 10 firm-year observations	30	401	13,458
Final sample with valid discretionary accrual estimates	30	401	13,458

Table 13: Estimation of the FLMJ and Other Jones-type Models

This table reports the estimation of the FLMJ model and the other Jones-type models in the validation sample. In Panel A, I report and compare the estimated coefficients and adjusted R-squares from the FLMJ model estimates in my study and in Dechow *et al.* (2003). In Panel B, I compare the estimation of the alternative Jones-type models in my study.

Panel A: Estimation of the FLMJ model

	Dechow et al. (2003)	**My study**
Sample period	1988-2000	1988-2006
Estimated *k*	0.070	0.072
β_1	0.022 (t=4.27)	0.044 (4.10)
β_2	-0.037 (t=-10.51)	-0.031 (-4.73)
β_3	0.212 (t=16.35)	0.219 (8.51)
β_4	0.042 (t=8.98)	0.025 (2.70)
$Adj.\ R^2$	0.200	0.253

Panel B: Specification and Estimation of Four Alternative Jones-type Models

Lagged Modified Jones Model:

$$Accrual_{it} = \alpha + \beta_1(\Delta sales_{i,t} - \Delta AR_{i,t}) + \beta_2 GPPE_{i,t} + \beta_3 Accrual_{i,t-1} + \varepsilon_{i,t}$$

Lagged Modified Jones Model:

$$Accrual_{it} = \alpha + \beta_1(\Delta sales_{i,t} - \Delta AR_{i,t}) + \beta_2 GPPE_{i,t} + \beta_3 Accrual_{i,t-1} + \varepsilon_{i,t}$$

FLMJ model without sales growth (FLMJ w/o SG):

$$Accrual_{it} = \alpha + \beta_1((1+k)\Delta sales_{i,t} - \Delta AR_{i,t}) + \beta_2 GPPE_{i,t} + \beta_3 Accrual_{i,t-1} + \varepsilon_{i,t}$$

FLMJ model:

$$Accrual_{it} = \alpha + \beta_1((1+k)\Delta sales_{i,t} - \Delta AR_{i,t}) + \beta_2 GPPE_{i,t} + \beta_3 Accrual_{i,t-1} + \beta_4 GR\_Sale_{i,(t\sim t+1)} + \varepsilon_{i,t}$$

Models	Industry-year obs.	α	β_1	β_2	β_3	β_4	$Adj.\ R^2$
Modified Jones	401	-0.058 (-9.20)	0.066 (4.40)	-0.040 (-5.49)			0.114
Lagged Model	401	-0.044 (-8.20)	0.066 (4.90)	-0.033 (-5.14)	0.202 (9.42)		0.211
FLMJ w/o SG	401	-0.050 (-10.02)	0.066 (6.16)	-0.028 (-4.38)	0.206 (9.40)		0.230
FLMJ	401	-0.046 (-8.11)	0.044 (4.10)	-0.031 (-4.73)	0.219 (8.51)	0.025 (2.70)	0.253

Table 14: Distribution of GAAP Violators in the DA Deciles

The table reports the distribution of GAAP violators in the discretionary accrual deciles, where the discretionary accruals are estimated using the Forward-Looking Modified Jones model and the GAAP violators are obtained from Erickson *et al.* (2004) for the period 1992 - 2001 and from Lane and O'Connell (2006) for the period 1994-2003.

DA decile	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**	**1998**	**1999**	**2000**	**2001**	**Total**
1				1			2	1	1	1	**6**
2								1	2		**3**
3					1		1	1			**3**
4						1		1			**2**
5				1				1			**2**
6			1		2			1			**4**
7	1					1			2	1	**5**
8		1				1		1			**3**
9						1	1		1		**3**
10				1			1		1		**3**
Total	**1**	**1**	**1**	**3**	**3**	**4**	**5**	**7**	**7**	**2**	**34**

Table 15: Validation of the Earnings Management Measure

This table reports the DTE and Special Items for loss-avoidance accrual manipulators and non-manipulators. Also reported are the differences in DTE and special items between the two manipulation groups.

Motivation to manipulate	**DTE**	**Special Items**
Manipulator	-0.0001	0.0025
Non-manipulator	-0.0021	-0.0261
Difference	0.002 (t = 2.574)	0.0286 (t = 10.89)

Table 16: Estimation of the Intrinsic Value Metrics in the Test Sample

The sample used to construct the intrinsic value metrics consists of 391,626 firm-years from the test sample. I use the FLMJ model to estimate discretionary accruals and report the sample statistics in Panel A; I use Ohlson (1995) as the valuation framework to estimate the intrinsic value metrics and report this estimation in Panel B. Panel C merges the two samples and constructs loss-avoidance accrual manipulators and non-manipulators.

Panel A: Construction of Intrinsic Value Metrics

	industries	**industry-years**	**firms**	**firm-years**
Obtain Data				
Test sample	74	1,693	20,823	391,626
Exclude financial and regulated industries (SIC code 4000-5000 and 6000-6999 and > 8000)	51	1,124	13,751	252,261
Match to CRSP	51	1,124	11,018	231,118
Match to IBES	51	1,124	7,853	179,148
Obtain book value per share	51	1,104	7,559	92,385
Obtain earnings data and earnings announcement date	51	1,093	7,419	76,419
Obtain analyst forecasts data	50	1,068	6,398	49,296
Construct the Intrinsic Value Measure				
Delete firm-years without lagged book value	50	1,067	6,356	48,828
Delete firms without lagged abnormal earnings	50	1,066	6,338	48,009
Estimate omega	50	1,021	6,227	46,628
Estimate gamma	50	930	5,886	42,838
Firm-years with intrinsic value estimates and stock price	50	930	5,845	37,701

Panel B: Estimation of FLMJ Model to Obtain DA Estimates

Steps	Industries	Industry-years	Firms	Firm-years
Raw data (test sample)	74	1,693	20,823	391,626
Exclude financial and regulated industries (SIC code 4000-5000 and 6000-6999 and > 8000)	51	1,124	13,751	252,261
Sufficient data for construct each variable in the FLMJ model	51	856	8,481	60,704
Exclude industry-years with less than 10 firm-year observations (required to estimate k for each industry-year)	43	719	8,421	60,110
Firm-years with valid discretionary accrual estimates	43	719	8,421	60,110

Panel C: Merge of the Intrinsic Value Measure and DA Measure Sample and Classification of Manipulators and Non-manipulators

Steps	Industries	Industry-years	Firms	Firm-years
Discretionary accrual Sample	43	719	8,421	60,110
Intrinsic value estimates sample	50	930	5,845	37,701
Merged intrinsic value and discretionary accrual samples	43	719	4,915	29,241
Construct the manipulator sample (firm-years with earnings greater than zero and earnings before discretionary accrual less than zero)	43	652	2,453	4,721
Construct matched non-manipulator sample (matched to the manipulator sample on firm size, industry, and year)	43	652	2,045	4,721
Sample for V, P, and V/P ratio analysis	43	652	3,170	9,442
Sample for returns analysis: (firms with February report month)	42	477	1,299	3,014

Table 17 – Sample Statistics: Earnings Management and Expectations Management
This table summarizes the yearly sample statistics for the expectations management sample (*i.e.*, firm-years with valid expectations management measure), earnings management sample (*i.e.*, firm-years with valid earnings management measure), and the joint sample (*i.e.*, firm-years with both earnings management and expectations management measures).

	Exp mgmt sample			Earn mgmt sample			Merged sample						
							Exp Manipulator			Earn Manipulate			Total merged sample
Fiscal year	Exp M	Exp N	Total	Earn M	Earn N	Total	Earn M	Earn N	Total	Exp M	Exp N	Total	
1988	32%	68%	1110	19%	81%	388	9%	91%	32	13%	88%	24	115
1989	44%	56%	1253	17%	83%	2736	19%	81%	346	48%	52%	138	795
1990	16%	84%	1361	17%	83%	2929	20%	80%	146	16%	84%	187	919
1991	38%	62%	1385	18%	82%	2976	19%	81%	380	41%	59%	182	966
1992	15%	85%	1432	22%	78%	3021	21%	79%	145	14%	86%	217	993
1993	26%	74%	1690	17%	83%	3211	18%	82%	305	29%	71%	193	1155
1994	14%	86%	1884	17%	83%	3424	22%	78%	174	19%	81%	204	1277
1995	39%	61%	2013	16%	84%	3540	17%	83%	528	42%	58%	210	1362
1996	24%	76%	2169	16%	84%	3755	15%	85%	350	22%	78%	228	1437
1997	18%	82%	2374	16%	84%	4169	17%	83%	285	19%	81%	259	1598
1998	29%	71%	2279	15%	85%	4163	16%	84%	463	32%	68%	240	1566
1999	22%	78%	1958	14%	86%	3994	12%	88%	286	17%	83%	208	1357
2000	22%	78%	1942	14%	86%	4031	16%	84%	296	25%	75%	184	1358
2001	33%	67%	1727	13%	87%	3869	15%	85%	411	35%	65%	173	1233
2002	10%	90%	1611	19%	81%	3693	23%	77%	124	12%	88%	250	1130
2003	40%	60%	1661	18%	82%	3500	23%	77%	459	45%	55%	235	1151
2004	20%	80%	1789	14%	86%	3416	21%	79%	229	26%	74%	192	1258
2005	50%	50%	603	13%	87%	3295	13%	87%	217	48%	52%	58	431
Total	**27%**	73%	30241	**16%**	84%	60110	**18%**	82%	5176 (27%)	**28%**	72%	3382 (17%)	20101

Table 18: V, P and V/P ratio Comparison for M and N

The loss-avoidance manipulator group is constructed by selecting firm-years with earnings greater than zero and earnings after discretionary accrual less than zero. The non-manipulator control sample is constructed by matching each firm-year in the manipulator sample with a firm-year in the non-manipulator sample on firm size (as measured by lagged total assets), industry (2-digit SIC code) and year. Using the 4,721 firm-years in the loss-avoidance manipulator sample and 4,721 firm-years in the non-manipulator sample, I compute the average price, intrinsic value estimate, and V/P ratio for each manipulation group and the differences in these statistics between the two groups across all years; I report these summary statistics here.

	Manipulator (M)	**Non-manipulator (N)**	**M - N**
Price	16.84	18.80	-1.97 (t=-4.39)
Intrinsic Value	10.79	10.39	0.40 (t=1.78)
V/P ratio	0.89	0.74	0.14 (t=5.11)
Lagged Price	16.41	16.14	0.27 (t=0.51)
Lagged Intrinsic value	10.35	9.72	0.63 (t=2.88)
Lagged V/P ratio	0.87	0.82	0.05 (t=1.64)

Table 19: V/P Ratio Portfolio Strategy Abnormal Returns after Controlling for Fama and French Risk Factors

The sample consists of 1,299 firms and 3,014 firm-years that report earnings in February. For each manipulation group in each year, I rank firms by V/P ratio and assign them into quintiles. I then compute average monthly quintile returns and regress the monthly returns of the top and bottom V/P quintiles on the three Fama and French risk factors and the momentum factor in the following regressions:

$$Ret_{m,t}^{Q5-M} = \alpha_{m,t}^{Q5-M} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q5-M}$$
$$Ret_{m,t}^{Q1-M} = \alpha_{m,t}^{Q1-M} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q1-M}$$
$$Ret_{m,t}^{Q5-N} = \alpha_{m,t}^{Q5-N} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q5-N}$$
$$Ret_{m,t}^{Q1-N} = \alpha_{m,t}^{Q1-N} + \beta_1 MktRF_{m,t} + \beta_2 SMB_{m,t} + \beta_3 HML_{m,t} + \beta_4 UMD_{m,t} + \varepsilon_{m,t}^{Q1-N}$$

This table reports the estimated coefficients from the above Fama and French returns regressions.

	Non-manipulator (N)			**Manipulator (M)**		
Dep. Var.	**Ret_Q5**	**Ret_Q1**	**Ret (Q5 - Q1)**	**Ret_Q5**	**Ret_Q1**	**Ret (Q5 - Q1)**
Intercept	0.009 (t=2.78)	0.005 (t=1.34)	**0.004 (t=3.17)**	0.004 (t=1.24)	0.003 (t=1.02)	**0.001 (t=0.74)**
mktrf	0.925 (t=10.26)	0.985 (t=9.07)	-0.059 (t=-1.79)	1.105 (t=12.80)	1.021 (t=12.15)	0.083 (t=2.94)
smb	0.755 (t=7.82)	1.002 (t=8.61)	-0.246 (t=-6.92)	0.909 (t=9.84)	0.953 (t=10.59)	-0.044 (t=-1.44)
hml	0.554 (t=4.65)	-0.320 (t=-2.23)	0.875 (t=19.91)	0.802 (t=7.03)	-0.139 (t=-1.26)	0.941 (t=25.11)
umd	-0.191 (t=-2.78)	-0.245 (t=-2.97)	0.054 (t=2.14)	-0.367 (t=-5.58)	-0.071 (t=-1.11)	-0.295 (t=-13.66)