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Income Classification Shifting and Financial Analysts’ Forecasts

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INCOME CLASSIFICATION SHIFTING AND FINANCIAL ANALYSTS' FORECASTS

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"Inch by inch, life's a cinch."

— *John Bytheway*

I dedicate this dissertation to my beloved parents, who have quietly stood by and made sacrifices while showering me with unconditional love and support through all these years of my pursuit of an academic career. To them I shall forever be indebted.

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ABSTRACT

Income classification shifting involves opportunistically misclassifying core expenses into nonrecurring items in order to boost core earnings. Recent studies have documented large sample evidence of its existence (e.g. McVay 2006; Fan et al.,2010; Barua et al.,2010). Managers engage in income classification shifting because they believe the market in general and financial analysts in particular focus on core earnings. If financial analysts are experts in forecasting permanent earnings, they should be expected to identify reported core earnings that have been inflated through classification shifting and revise their future earnings forecast accordingly. Consistent with my prediction, I find that given the same amount of earnings news, analysts revise their future quarterly earnings forecasts by half as much for classification shifters than for non-classification shifters, suggesting analysts recognize that income classification shifters' core earnings are less likely to persist into the future. However, I also find that analysts fail to fully gauge the impact of classification shifting on future earnings, leading to more optimistically biased forecasts for classification shifters. Finally, classification shifting makes it more difficult for analysts to forecast earnings so that their forecasts become less accurate.

1. INTRODUCTION

This study examines whether financial analysts can identify income classification behavior and how they respond to such behavior as reflected in their future earnings forecasts. Income classification shifting refers to a type of earnings management technique used to inflate core earnings by intentionally misclassifying core expenses such as cost of goods sold and selling and administrative expenses as non-recurring items. Management has incentives to boost core earnings because core earnings are typically valued higher than non-core earnings. As core earnings, by definition, should reflect the performance of regular business operations that is more likely to persist in the future, they are weighted more in firm valuation than other non-recurring earnings components. Therefore, both the academics and practitioners have emphasized the importance of using core earnings in the valuation of firms. In fact, security analysts are known to exclude certain nonrecurring or unusual components from their forecasts of earnings, which are often referred to as "street earnings" (Bradshaw and Sloan 2002; Gu and Chen 2004). Given the significant market consequences of meeting/beating analyst expectations (Bartov et al. 2002; Kasznik and McNichols 2002; Skinner and Sloan 2002), it is not surprising that management is found to use classification shifting to hit analyst earnings forecast benchmarks (McVay 2006; Barua et al. 2010; Fan et al. 2010). However, with classification shifting, the core earnings are artificially hyped when recurring expenses are removed.[1] An interesting question then becomes are analysts able to adjust for the temporary effects of the income classification shifting as reflected in their earnings forecasts? How will income classification shifting affect the attributes of their forecasts?

[1] Assume a firm's core earnings pre classification shifting is $1. Further assume the firm's core earnings is a perpetuity discounted at 10%, then the present value of the core earnings should be $10. After moving $0.2 of core expense into special items, its core earnings post shifting is now $1.2. The present value of the core earnings now becomes $12. If the firms is valued based only on the valuation of core earnings, then it will be overvalued.

The motivation for this study is to increase our understanding of the impact of income classification shifting on market participants. Income classification shifting is recently recognized as the third form of earnings management in addition to accrual management and real earnings management (McVay 2006; Fan et al. 2010). While the literature on accrual management and real earnings management is large and extensive, studies on income classification shifting are relatively sparse and limited. However, there is evidence that income classification shifting may have significant economic consequences. For instance, McVay (2006) find that in her sample, on average $287 thousand of regular operating expenses are shifted to special items per firm annually, resulting in an average increase in their core earnings by half a cent per share. Firms with income-decreasing special items of at least 5% of sales shift an average of $1.66 million per firm per year, or roughly three cents per share. In addition, the SEC has also expressed concerns over the proper classification of accounting items in financial statements and has frequently filed civil law suits against firms charged with misclassification of ordinary operating expenses as non-recurring expenses.[2] Apparently, the SEC is concerned that income classification shifting can potentially mislead investors and impair market efficiency. As financial analysts are important users of financial statement information, understanding how income classification shifting affects analysts' information outputs should be of interest to regulators, investors, and academics.

This study also aims to extend the literature on analysts' ability to identify earnings management and incorporate it into their reports. The academic literature has documented extensive evidence of earnings management; however, our understanding of how financial analysts deal with potential earnings management and its impact on their earnings forecasts is

[2] For SEC Accounting and Auditing Enforcement release regarding financial reporting related enforcement actions brought by the SEC in federal court, please go to http://www.sec.gov/divisions/enforce/friactions.shtml .

quite limited. For instance, Burgstahler and Eames (2003) have shown that analysts impound their expectation of earnings management to avoid small losses in their forecasts, even though they fail to identify specific instances of such earnings management. They call for research that examines whether alternative forms of earnings management are also reflected in analyst forecasts. Shane and Stock (2006) find that analysts seem to be unable to appreciate the temporary earnings effects from earnings management that shifts income from fourth quarters in higher tax rate years to immediately following first quarters of lower tax rate years. They also call for research to investigate analysts' ability to adjust for the earnings effects of earnings management in various contexts. Income classification shifting therefore provides an interesting setting to examine the above issues because management engages in income shifting as a response to the way analysts process earnings numbers. It could potentially provide additional insight as to the role of earnings management in analysts' reports.

To identify firms that are likely to engage in income classification shifting, I develop a classification scheme base on prior literature (McVay 2006; Fan et al. 2010). McVay (2006) documents the existence of income classification shifting by showing a positive relation between unexpected core earnings and negative special items and a negative relation between unexpected change in future core earnings and negative special items. I adopt the quarterly core earnings expectation model developed by Fan et al. (2010) and devise the expected quarterly core earnings changes model based on McVay (2006) and Fan et al. (2010). I then classify a firm as a classification shifter if it has positive unexpected core earnings, negative special items and negative unexpected change in core earnings.

To investigate whether financial analysts recognize that the core earnings of income classification shifters are artificially boosted, I examine financial analysts' quarterly earnings forecast revisions. I find that for the same amount of earnings news, financial analysts revise their earnings forecasts by only half as much for classification shifters than for non-classification shifters, suggesting that they discount the earnings reported by shifters. However, financial analysts' earnings forecasts are still on average optimistic for classification shifters, indicating that they fail to assess the full amount of the earnings inflated in classification shifting. Finally, I find that income classification shifting causes financial analysts' forecast accuracy to deteriorate. These results are robust to a battery of tests

The rest of the paper proceeds as follows. Section 2 provides literature review and develops the hypotheses. Section 3 describes the research design. Section 4 discusses the data and presents the results. Section 5 concludes.

2. BACKGROUND AND LITERATURE REVIEW

2.1 Income Classification Shifting

Income classification shifting refers to management's intentional misclassification of core expenses such as cost of goods sold, sales and administrative expenses, into non-recurring items, including special items and discontinued operations, in an attempt to boost core earnings. It has been recently recognized as a third type of earnings management tool studied in the literature. Current research recognizes that compared with accruals management and real earnings management, income classification shifting confers management the following advantages. First of all, income classification shifting is more difficult to detect. Under current accounting rules, the classification of expense items can be subjective. It is difficult for auditors to identify inappropriate classification. Furthermore, as income classification shifting does not change the bottom-line earnings number, auditors have less incentive to uncover the related accounts involved in classification shifting. Secondly, income classification shifting is less costly to implement. Compared to real earnings management, where real economic activities or transactions are affected, there will be no adverse economic consequences for income classification because it involves only pure accounting treatment. Unlike accruals management, which is also a type of accounting manipulation, allocation of accounting items within the income statement does not involve accruals that need to be reversed later. Therefore, income classification shifting can be a viable tool in management's repertoire to meet market expectations or achieve economic gains (Nelson et al. 2002; McVay 2006; Barua et al 2010).

Recent research has provided evidence of the use of income classification shifting by management. For instance, drawing on annual US data, McVay (2006) finds a positive correlation between unexpected core annual earnings and income-decreasing special items, suggesting that core expenses are shifted to special items to inflate core earnings. Fan et al.

(2010) extends McVay (2006) to quarterly earnings and documents stronger evidence of classification shifting in the fourth quarter than in interim quarters. Barua et al. (2010) further show that management also shift core expenses to income-decreasing discontinued operations to inflate core earnings. Apparently, income classification shifting occurs outside the US as well. Athanasakou et al (2007) find that large firms in the United Kingdom engage in classification shifting of core expenses to other non-recurring items to meet analyst forecasts. Haw et al (2011) document pervasive use of misclassification among firms in East Asian countries to overstate core earnings. There appears to be substantial evidence to validate the existence of classification shifting both in the US and around the world.

As an earnings management apparatus, income classification shifting has been associated with various capital market incentives. Most notably, there exists evidence that classification shifting is used to meet analyst forecasts (McVay 2006; Barua et al. 2010; Fan et al. 2010)[3]. This is plausible because analysts are known to focus on "street earnings" or core earnings in their analysis and forecasts (Bradshaw and Sloan 2002; Doyle et al. 2003; Gu and Chen 2004).[4] Classification shifting can boost such earnings significantly. McVay (2006) documents that for firms with income-decreasing special items of at least 5% of sales, classification shifting can increase core earnings by three cents per share. Classification shifting is also more likely to happen in the fourth quarter for firms that just meet or beat analyst forecast (Fan et al., 2010). In fact, in both UK and East Asia, meeting analyst forecasts has been cited as one of the major incentives for management to misclassify core expenses as special items (Athanasakou et al.

[3] McVay (2006) finds that firms are more likely to engage in classification shifting when it enables them to meet or beat analyst forecasts. However, it does not examine how classification shifting affects analyst forecasts for the next period, which is the focus of this study.

[4] Bradshaw and Sloan(2002) find that street earnings as reported by analyst tracking agencies such as IBES are diverging from GAAP earnings in the recent years and are more value relevant than GAAP earnings as well.

2007; Haw et al. 2011). Finally, there is also initial evidence of the manipulation of core earnings around seasoned equity offerings (Siu and Faff 2012).

2.2 Earnings Management and Analysts' Forecasts

Financial analysts play an important role in the capital markets. As information intermediaries, analysts are considered sophisticated users of financial information that analyze and interpret accounting data in formulating their forecasts. Analyst forecasts predict future earnings more accurately than time-series models (Brown et al. 1987 a,b). They are also less biased than the earnings expectations implied by stock prices (Mendenhall 1991; Ababanell and Bernard 1992). Because their forecasts can have significant impact on market earnings expectations with substantial financial consequences (Skinner and Sloan 2002), management has great incentives to meet those market expectations. Earnings management is one way for management to achieve such earnings targets.

Current literature, however, offers no consistent evidence as to whether analysts are efficient in identifying earnings management and incorporating it in their earnings forecasts. Ettredge et al. (1995) document that analysts seem to be able to draw on additional information to identify ex ante possible overstatement in quarterly earnings and effectively eliminate one fifth of the dollar amount of the overstatements in their earnings forecast revisions following the most recent quarterly earnings announcement. Burgstaler and Eames (2003) investigate the issue in the case of earnings management to avoid losses and small earnings decreases as documented in Burgstahlaer and Dichev (1997). Basically, they examine the distribution of analysts' earnings forecasts around zero and find a similar pattern to the one in realized earnings. Specifically, their forecast of earnings levels and changes contain fewer observations to the left of zero and more observations to the right of zero, resulting in a kink in the forecast distribution around zero. Such evidence is interpreted as suggesting that analysts anticipate earnings management to avoid losses and earnings decrease and include such earnings management in their forecast. However, analysts do not seem to be capable of identifying specific instances of earnings management at the firm level, leading to forecast optimism at zero earnings forecasts and forecast pessimism at zero earnings realizations. In other words, they tend to predict earnings management that is not realized and fail to predict earnings management that is realized.

Considering that firms manage earnings in response to analysts' forecasts, Liu (2006) posits that analysts are aware of these earnings management practices, and incorporate such expected behavior into their forecasts. Assuming analysts aim to minimize their forecast errors, she documents that analysts systematically forecast below (above) the otherwise non-strategic forecasts(forecasts of earnings that have not been managed to meet or beat analyst' forecasts) for firms that are more likely to manage earnings downward (upward). Using a sample of earnings restatements and cases where upward earnings management is most likely, Givoly et al. (2010) show that analysts' forecasts are more closely related to the managed earnings, suggesting that analysts forecast the managed earnings number. They also issue more optimistic earnings forecasts and more positive recommendations in cases of upward earnings management, which are unwarranted given subsequent performance. These results make it difficult to draw definitive conclusions on whether analysts are capable of detecting earnings management. Arguing that analysts should be more concerned with forecast informativeness than forecast accuracy, Louis et al. (2012) find analysts' deviations from management pre-announced earnings are negatively associated with abnormal accruals, indicating that analysts intend to forecast the unmanaged earnings when they perceive that management earnings guidance involves earnings management. Such finding therefore suggests when management earnings guidance differs from analyst forecasts, analysts are able to tell whether earnings management exists and forecast what they consider the “true” earnings number. However, it is not obvious whether analysts can detect earnings management when no management guidance exists.

In fact, Bradshaw et al. (2001) document that analysts’ earnings forecast errors are negatively associated with the level of accruals, indicating that on average analysts do not completely understand that higher accruals are associated with lower future earnings. Assuming these extreme accruals result from earnings management, then such a finding implies that analysts cannot effectively appreciate the implications of accruals for earnings management.

There is also evidence that not only do analysts fail to detect broad accruals management, they also lack the ability to recognize specific types of earnings management. For instance, Shane and Stock (2006) find that analysts do not account for the effects of income shifted from higher tax rate years to lower tax rate years in their earnings forecasts. Both Chaney et al. (1999) and Hanna and Orpurt (2006) find that analyst forecast accuracy decreases and forecast dispersion increases when firms report nonrecurring items including restructuring charges. As earnings manipulation is highly susceptible in those instances, these results suggest that analysts cannot efficiently adjust their forecasts for earnings management.

3. HYPOTHESIS DEVELOPMENT

3.1 Income Classification Shifting and Analyst Forecast Revision

When firms engage in income classification shifting, their current period core earnings is overstated by the core expenses, which will recur in the next period, leading to lower future core earnings. Consequently, these core earnings are unlikely to persist into the future. After firms make earnings announcements each quarter, analysts reassess their earnings forecasts for future periods. If a firm's actual earnings are greater (lower) than analysts' expectations, then analysts may revise their forecasts of the firm's future earnings upward (downward). The magnitude of the forecast revision is a function of the persistence of the forecast error (Easton and Zmijewski 1989). In other words, analysts are expected to respond more to permanent earnings and less or little to transitory earnings. If analysts are able to recognize that the earnings news in classification shifters' core earnings are less persistent, they will adjust their forecasts to a lesser degree. On the other hand, if they are unable to identify or unwilling to incorporate such classification shifting behavior into their forecasts, then ceteris paribus their forecast revisions will not differ between classification shifters and non-shifters. In order to examine whether analysts' forecast revisions reflect the lower persistence of classification shifters' current earnings news, I test the following hypothesis:

H1: Ceteris Paribus, financial analysts adjust their quarterly earnings forecast revisions to a lesser degree for income classification shifters than for non-shifters.

3.2 Income Classification Shifting and Analyst Forecast Bias and Accuracy

Even though analysts may respond less to classification shifters' earnings news, it is unlikely that they will be able to accurately estimate the full extent of shifters' manipulated earnings. As a result, I expect their forecast errors to be more optimistically biased for income classification shifters. In addition, earnings manipulation involved in classification shifting makes it more difficult to forecast earnings. Hence I expect analyst forecast accuracy to decline for classification shifters. I therefore make the following predictions regarding analysts' forecast error with regard to income classification shifting.

> H2a: Ceteris paribus, financial analysts' quarterly earnings forecasts are more optimistically biased for income classification shifters than for non-shifters.

> H2b: Ceteris paribus, financial analysts' quarterly earnings forecasts are less accurate for income classification shifters than for non-shifters.

4. RESEARCH DESIGN

4.1 Measuring Income Classification Shifting

4.1.1 McVay (2006) Model

When managers shift core expenses to non-recurring items, their core earnings are artificially inflated. We would therefore expect a positive relation between classification shifters' unexpected core earnings and the magnitude of the negative special items. Based on this idea, McVay (2006) is able to document large sample empirical evidence of the existence of classification shifting. To capture income classification shifting, McVay (2006) develops a two-step equation system. The first step involves an expected core earnings level and changes model.

$$CE_t = \beta_0 + \beta_1 CE_{t-1} + \beta_2 ATO_t + \beta_3 ACCRUALS_{t-1} + \beta_4 ACCRUALS_t + \beta_5 \Delta SALES_t + \beta_6 NEG\_\Delta SALES_t + \varepsilon_t \quad (1)$$

$$\Delta CE_t = \phi_0 + \phi_1 CE_{t-1} + \phi_2 \Delta CE_{t-1} + \phi_2 \Delta ATO_t + \phi_3 ACCRUALS_{t-1} + \phi_4 ACCRUALS_t + \phi_5 \Delta SALES_t + \phi_6 NEG\_\Delta SALES_t + \varepsilon_t \quad (2)$$

Where:

CE_t=(Sales – COGS – SGA expenses)/Sales
ATO_t=Asset Turnover Ratio (Sales/Average NOA)
$Accruals_t$=(Net Income before Extraordinary Items – CFO)/Sales
$\Delta Sales_t$=% change in Sales from year t-1 to t
$NEG\_\Delta SALES_t$=1 if $\Delta Sales_t$ is negative, and 0 otherwise
UE_CE_t=Reported core earnings minus expected core earnings
SI_t=Income-decreasing special items/Sales

The core earnings level model includes lagged core earnings, CE_{t-1}, because core earnings are likely to persist. Asset Turnover Ratio, ATO_t, is included because it is found to be negatively related to profit margins (Nissim and Penman 2001). The definition of core earnings in this model is close to profit margins. Both current and lagged accrual levels($Accruals_t$, $Accruals_{t-1}$) are associated with firm performance (Sloan 1996; DeAngelo et al. 1994), they are included as controls. Even core earnings is scaled by sales, sales growth ($\Delta Sales_t$) is included because as sales grow, fixed costs become smaller per sales dollar. As costs increase more when activity arises than they decrease when activity falls by the same amount(Anderson et al., 2003), $NEG\_\Delta SALES_t$ is introduced to allow the slope to differ between sales increase and decreases.

The change in core earnings model includes both lagged core earnings, CE_{t-1}, and the change in core earnings from year t-2 to t-1, ΔCE_{t-1} so that the degree of mean reversion varies in the model based on prior year's level of core earnings(Freeman, et al., 1982; Fama and French 2000). In addition, they are included because both levels and changes are used to forecast changes in profitability (Fama and French 2000; Fairfield and Yohn 2001; Penman and Zhang 2002). In addition, level of asset turnover is replaced with change in asset turnover(ΔATO_t). The remaining variable in the level model stay in the changes model.

These two models are run cross-sectionally by industry and fiscal year. The predicted values from the model measure expected core earnings, CE_t, and expected change in core earnings, ΔCE_t, respectively. The difference between reported (changes in)core earnings and expected (changes in) core earnings yield unexpected core earnings (UE_CE_t) and unexpected change in core earnings($UE\_\Delta CE_t$).

If managers shift core expenses to non-recurring items, we should expect a positive relation between classification shifters' unexpected core earnings and the magnitude of the negative special items. To document such relation, in the second step, McVay (2006) estimates the following two regressions:

$$UE\_CE_t = \alpha_0 + \alpha_1 \%SI_t + \varepsilon_t \qquad (3a)$$

$$UE\_\Delta CE_{t+1} = \alpha_0 + \alpha_1 \%SI_t + \varepsilon_t \qquad (3b)$$

In the first equation 3a, the coefficient α_1 is expected to be positive if income classification shifting does occur. However, firms with negative special item may experience restructuring or other economic event that results in real performance improvement. To rule out such alternative explanation, future unexpected change in core earnings is regressed on negative special items and the coefficient is expected to be negative. The rationale is that firms that classification shift is expected to have a lower than expected change in core earnings in year t+1 with large special items in year t.

4.1.2 Fan et al. (2010) Model

One of the major limitations of the McVay (2006) model is that the positive relation between expected core earnings and special items may be driven mechanically by the inclusion of current accruals. The inclusion of accruals is aimed to control for extreme firm performance. However, accruals may also contain special item accruals. Therefore, high special item accruals drive down expected core earnings and result in higher unexpected core earnings, which is positively related to special items in the second step regression. In fact, when accruals are taken out of the model, the relation between unexpected core earnings and special items becomes negative (McVay, 2006). Such criticism of the McVay(2006) model leads to the development of refined core earnings level model by Fan et al.(2010) as stated below:

$$CE_q = \beta_0 + \beta_1 CE_{q-1} + \beta_2 CE_{q-4} + \beta_3 ATO_q + \beta_4 ACCR_{q-1} + \beta_5 ACCR_{q-4} + \beta_6 \Delta SALES_q + \beta_7 NEG\_\Delta SALES_q + \beta_8 RETURNS_q + \beta_9 RETURNS_{q-1} + \varepsilon_q \quad (4a)$$

The major differences between the Fan et al. (2010) and the McVay (2006) model are twofold. First of all, current accruals are removed and only lagged accruals are retained. Second, both the current period returns, $RETURNS_q$, and last period returns $RETURNS_{q-1}$, are added to the model as controls for performance. This model therefore relieves the concern that the positive relation between unexpected core earnings and special items is mechanical. As the paper seeks to examine whether income classification shifting differs between the fourth quarter and the other three quarters, the model is run using quarterly data.

4.1.3 Identifying Income Classification Shifters

In order to identify income classification shifters, I adopt the core earnings level model as developed Fan et al. (2010) using quarterly data . In addition, drawing on the McVay (2006) and Fan et al. (2010) model, I devise the quarterly core earnings changes model as follows:

$$\Delta CE_q = \delta_0+\delta_1 CE_{q-1} +\delta_2\Delta CE_{q-1}+\delta_3 CE_{q-4} +\delta_4\Delta CE_{q-4} +\delta_5 ATO_q +\delta_6 ACCR_{q-1}+\delta_7 ACCR_{q-4} +\delta_8\Delta SALES_q +\delta_9 NEG\_\Delta SALES_q +\delta_{10} RETURNS_q+\delta_{11} RETURNS_{q-1}+\nu_q \quad (4b)$$

The model is estimated cross sectionally by industry and fiscal year. The difference between reported changes in core earnings and the expected change in core earnings as predicted from the model yields unexpected change in core earnings($UE\_\Delta CE_{t+1}$). As discussed above, for classifications shifters, their unexpected core earnings(UE_CE_t) are expected to be positively related to special items in t and their unexpected change in future core earnings($UE\_\Delta CE_{t+1}$) are expected to be negatively related to special items in t. Therefore, I classify firms as income classification shifters if they have positive UE_CE_t, negative $\%SI_t$ and negative $UE\_\Delta CE_{t+1}$.

4.2 Income Classification Shifting and Analysts' Forecasts

4.2.1 Analyst Forecast Revisions

To examine whether analysts can identify and incorporate income classification shifting behavior in their forecast revisions, I estimate the following regression for our sample of firms for all quarters between 1988 and 2010:

$$FREV_{i,q}^{q+1}=\gamma_0+\gamma_1 FE_{i,q}+\gamma_2 SHIFT_{i,q}+\gamma_3 FE_{i,q}*SHIFT_{i,q}+\gamma_4 JustMET_{i,q}+\gamma_5 LOSS_{i,q} +\gamma_6 REST_{i,q}+\text{Industry Dummies}+e_{i,q+1} \quad (5)$$

Where:

$FREV_{i,q}^{q+1}$= Analyst Forecast Revision, calculated as the difference between the first analyst mean forecast for quarter q+1 after the earnings announcement in quarter q and the last analyst mean forecast for quarter q+1 before earnings announcement in quarter q, scaled by beginning of period stock price.

$FE_{i,q}$ = Analyst Forecast Error, calculated as the difference between I/B/E/S actual EPS and the last analyst mean forecast for quarter q, scaled by beginning of period stock price.

$SHIFT_{i,q}$ = 1 if the firm has positive unexpected core earnings and negative special items in quarter q and negative unexpected change in core earnings in quarter q+1.

$JustMET_{i,q}$ = 1 if the firm reported an earnings forecast error equal to $0.00 or $0.01.

$LOSS_{i,q}$ = 1 if operating income before depreciation(oibdpq) in quarter t is less than zero, 0 otherwise

$REST_{i,q}$ = 1 if the firm reported a restructuring charge in quarter t, 0 otherwise

Analysts revise earnings estimates based on earnings news. Therefore, analyst forecast error, $FE_{i,q,}$ is included to control for earnings surprise. Firms are more likely to classification shift when it enables them to meet analyst earnings forecast (McVay 2006; Fan et al. 2010). I include a dummy $JustMET_{i,q}$ to control for analyst forecast revision for firms that just meet or beat analyst earnings forecasts(Kaznik and McNichols 2002). Previous research has found that analysts tend to overpredict earnings to a greater degree for firms suffering from losses or negative stock returns (Ali et al. 1992; Klein 1990). Therefore, I include a dummy variable for firms that report an operating loss in quarter q. Finally, firms that classification shift have negative special items. These special items may include restructuring charges. Chaney et al. (1999) find that analysts' forecast revision of next period's earnings is on average negative for firms that announce restructuring charges. Therefore, I include a dummy variable for firms that have non-zero restructuring charges. I also include industry dummies to control for any industry effects on analyst forecasts.

If analysts recognize that income classification shifter's core earnings have lower persistence, they would revise their forecasts to a lesser degree. Therefore, I would expect the coefficient on $Shift_q$, $\gamma_{2,}$ to be negative. Further, I would predict the coefficient on the interaction term $FE_{i,q}$*$SHIFT_{i,q}$, γ_3, to be negative, meaning that for the same amount of earnings news, analyst earnings revisions would be lower for shifters than for nonshifters.

4.2.2 Analyst Forecast Bias and Accuracy

To examine the bias and accuracy of analysts' forecasts for classification shifters, I estimate the following regressions.

$$FE_{i,q+1}=\lambda_0+\lambda_1 FE_{i,q}+\lambda_2 SHIFT_{i,q}+\lambda_3 ACCR_{i,q}+\lambda_4 REST_{i,q}+\lambda_5 REST_{i,q+1}+\lambda_6 RET_{i,q}+\lambda_7 RET_{i,q+1} +\lambda_8 NANALYS_{i,q+1}+\lambda_9 SIZE_{i,q+1}+\mu_{i,q+1} \quad (6)$$

$$|FE_{i,q+1}|=\alpha_0+\alpha_1|FE_{i,q}|+\alpha_2 SHIFT_{i,q}+\alpha_3 ACCR_{i,q}+\alpha_4 REST_{i,q}+\alpha_5 REST_{i,q+1}+\alpha_6 RET_{i,q} +\alpha_7 RET_{i,q+1}+\alpha_8 NANALYS_{i,q+1}+\alpha_9 SIZE_{i,q+1}+\xi_{i,q+1} \quad (7)$$

Where:

$FE_{i,q+1}$ = Analyst Forecast Error, calculated as the difference between I/B/E/S actual EPS[5] and the first analyst mean forecast for quarter q+1, scaled by beginning of period stock price.

$FE_{i,q}$ = Analyst Forecast Error, calculated as the difference between I/B/E/S actual EPS and the last analyst mean forecast for quarter q, scaled by beginning of period stock price.

$|FE_{i,q+1}|$ = Forecast Accuracy, calculated as the absolute value of analyst forecast error for quarter q+1, FE_{q+1}, scaled by beginning of period stock price

$|FE_{i,q}|$ = Forecast Accuracy, calculated as the absolute value of analyst forecast error for quarter q, FEq, scaled by beginning of period stock price

$SHIFT_{i,q}$ = 1 if the firm has positive unexpected core earnings and negative special items in quarter q and negative unexpected change in core earnings in quarter q+1.

$ACCR_{i,q}$ = Operating Accruals, calculated as net income before extraordinary items (ibq) minus cash from operations (oancfy), scaled by $Sales_q$.

$REST_{i,q}$ = 1 if the firm reported a restructuring charge in quarter q, 0 otherwise

$SI_{i,}$ = 1 if the firm reported a restructuring charge in quarter q+1, 0 otherwise

[5] According to Bradshaw and Sloan (2002), IBES would regularly exclude such charges as restructuring charges, write-downs and impairments, research and development expenditures, merger and acquisitions costs, mandatory stock compensation expense, goodwill amortization, and certain results of subsidiaries.

$RET_{i,q}$ = Three-month market-adjusted value weighted return exclusive of dividends corresponding to the fiscal quarter q

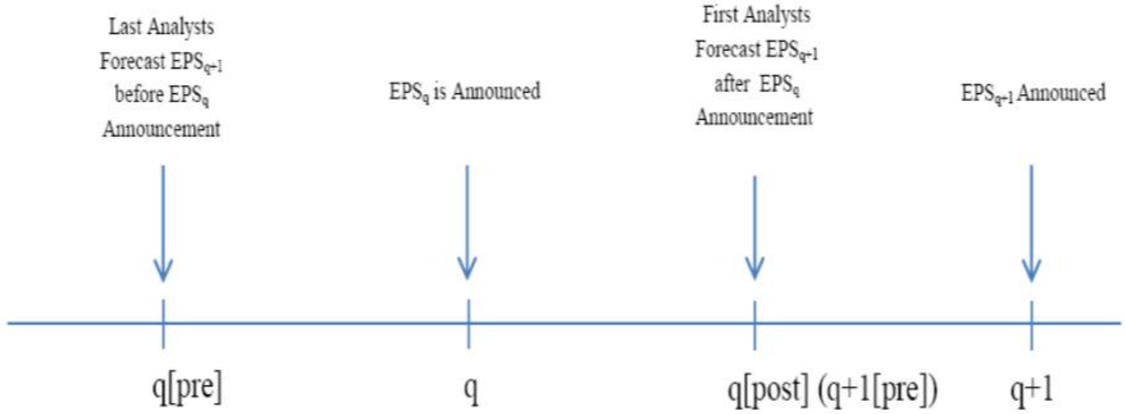
$RET_{i,q+1}$ = Three-month market-adjusted value weighted return exclusive of dividends corresponding to the fiscal quarter q+1

$NANALYS_{i,q+1}$= Log of the number of analysts forecasts included in the I/B/E/S mean forecast

$SIZE_{i,q+1}$ = Log of the total market value of firm i at the beginning of quarter q+1

I include lagged forecast errors because previous research has shown that analysts' forecasts exhibit positive serial correlation (Ali et al., 1992). Operating accruals are included because Bradshaw and Sloan (2002) document that analyst forecast errors are negatively correlated with accruals. Chaney et al. (1999) found that analyst forecasts are biased upward subsequent to restructuring charges, so I include a dummy variable, $REST_{i,q}$, to control for the effect of restructuring charges on analyst forecast. Previous research has also documented that the optimistic bias in analyst forecast increases for firms that exhibit large non-recurring charges (Hanna and Opurt 2006), so I include SI_q as a control variable. Market returns are included because there exists evidence that analysts do not use past stock return information efficiently in their forecasts (Ali et al., 1992). Finally, both high analyst following and large firm size have been shown to be associated with lower forecast error and greater forecast accuracy due to richer public information environment (Lys and Soo 1995; Alford and Berger, 1998).

If analysts cannot fully adjust their earnings forecasts for the amount of misclassified core expenses, then their forecasts for classification shifters will be even more optimistically biased. Therefore, I expect a negative coefficient on $SHIFT_{i,q}$ in the forecast bias regression. Earnings manipulation through classification shifting will make it more difficult to accurately predict future earnings. Therefore, I expect a positive coefficient on $SHIFT_{i,q}$ in the forecast accuracy regression.



$$FREV_q^{q+1} = \text{Forecast}_{q+1}^{q+1}[\text{First}] - \text{Forecast}_{q}^{q+1}[\text{Last}]$$

$$FE_q^q \quad = \text{Actual}_q - \text{Forecast}_q^q[\text{Last}]$$

$$FE_{q+1}^{q+1} \quad = \text{Actual}_{q+1} - \text{Forecast}_{q+1}^{q+1}[\text{First}]$$

Figure 1_Timeline for Measuring Forecast Revision and Forecast Error

5. SAMPLE SELECTION AND DESCRIPTIVE STATISTICS

5.1 Sample Selection

Data are obtained for the years 1988 to 2010 from the Compustat Industrial Quarterly File, I/B/E/S Split-Unadjusted File, and CRSP monthly return file. Following McVay (2006), I remove firm-quarter observations with annual sales of less than $1 million to avoid creating outliers as a result of scaling variables by sales. To ensure quarterly data are comparable across years, I eliminate firms that had a change in fiscal year. Finally, I require at least 15 observations per industry-year-quarter to estimate expected core earnings. Industries are classified based on Fama and French (1997). The full sample for the core earnings regressions has 126,427 firm-quarter observations and 6,987 unique firms. The subsample for analysts' forecasts has 70,306 firm-quarters and 4,799 unique firms.

5.2 Descriptive Statistics

The Appendix provides the definitions of the variables used in the analyses. Table 1 presents the descriptive statistics for the variables used in the core earnings regression to classify classification shifters (Panel A) and for the variables used in the analyst forecast regressions (Panel B). Panel A shows that the mean (median) of core earnings for all firm quarters as scaled by sales is 0.096 (0.101). The mean (median) of special items as a percentage of sales is 2.09 (0.0) percent. Panel B shows that analysts' earnings forecast revision of the next period is on average negative (-0.002). Consistent with prior research that analysts forecasts are optimistic on average, analysts' forecast errors for current period (FE_q) and next period (FE_{q+1}) are negative (-0.003 and -0.004, respectively). About 11.7% of the firm quarters are classified as shifters whereas 15.9% of the firm quarters meet or beat analyst forecast by 1 cent. Finally, 13.4% of the firm quarters had a loss, and 10.2 % of the firm quarters reported restructuring charges.

Table 1

Descriptive Statistics

Panel A: Descriptive Statistics for Relevant Variables Used to Classify Shifters

Variable	Mean	Median	Standard Deviation	1%	99%
CE_q	0.096	0.101	0.234	0.040	0.185
CE_{q-1}	0.098	0.101	0.231	0.040	0.185
CE_{q-4}	0.095	0.102	0.245	0.041	0.187
UE_CE_q	0.001	0.002	0.124	-0.032	0.039
$\Delta CE_{q-1,q}$	-0.001	0.000	0.135	-0.025	0.025
$\Delta CE_{q,q+1}$	-0.002	0.000	0.129	-0.025	0.024
$UE\_\Delta CE_{q-1,q}$	0.002	0.001	0.325	-0.043	0.048
$UE\_\Delta CE_{q,q+1}$	-0.001	0.001	0.309	-0.042	0.046
$\%SI_q$	2.09%	0.00%	9.02%	0.00%	0.00%
ATO_q	2.156	0.924	4.283	0.393	2.012
ΔATO_q	0.048	0.003	2.541	-13.619	15.293
$ACCR_{q-1}$	-0.170	-0.094	0.458	-0.289	0.024
$ACCR_{q-4}$	-0.163	-0.093	0.469	-0.290	0.027
$\Delta SALES_q$	12.13%	6.95%	0.352	-4.77%	21.29%
$NEG\_\Delta SALES_q$	-0.055	0.000	0.119	-0.048	0.000
$RETURNS_q$	0.007	-0.013	0.225	-0.113	0.094
$RETURNS_{q-1}$	0.007	-0.013	0.222	-0.113	0.094

Panel B: Descriptive Statistics for Variables Relevant for Analyst Forecast Regressions

Variable	Mean	Median	Standard Deviation	1%	99%
$FREV_q^{q+1}$	-0.002	0.000	0.008	-0.050	0.016
FE_q	-0.003	0.000	0.019	-0.126	0.044
FE_{q+1}	-0.004	0.000	0.024	-0.169	0.051
$\|FE_q\|$	0.008	0.002	0.021	0.000	0.154
$\|FE_{q+1}\|$	0.010	0.002	0.027	0.000	0.203
$SHIFT_q$	0.117	0.000	0.322	0.000	1.000
$\Delta EARN_q$	-0.013	-0.002	0.056	-0.261	0.238
$JustMET_q$	0.159	0.000	0.366	0.000	1.000
$NANALYS_{q+1}$	1.368	1.386	0.933	0.000	3.219
$LOSS_q$	0.134	0.000	0.340	0.000	1.000
$REST_q$	0.102	0.000	0.303	0.000	1.000
$RESTCH_q$	-0.001	0.000	0.004	-0.031	0.000
$Size_{q+1}$	6.040	5.945	1.711	2.510	10.664

See Appendix for variable definitions. The full sample consists of 126,427 firm-quarter observations.The sample for analysts' forecasts has 70,306 firm-quarter observations. All variables except indicator variables are winsorized at 1st and 99th percentiles.

Table 2 compares the shifters and non-shifters on selective firm characteristics. The current quarter core earnings for shifters are significantly larger for shifters than for non-shifters possibly due to shifting (0.153 vs. 0.138). By design, shifters also have much higher positive unexpected core earnings(0.058 vs. -0.004) and much lower negative unexpected change in core earnings in the next quarter(-0.122 vs. 0.010). They also tend to have larger negative special items as a percentage of sales (3.85% vs. 1.56%). 19.4% of shifter-quarters have restructuring charges compared to only 9% for non-shifter quarters. Finally, shifters on average are larger than non-shifters, consistent with McVay (2006).

Table 2
Selective Descriptive Statistics for Shifters/Non-Shifters

Variable	Shifters (N=8,241) Mean	Shifters Median	Non-Shifters (N=62,065) Mean	Non-Shifters Median	p-value for statistical difference between shifters and non-shifters: t-test	Wilcoxon Rank Sum Test
CE_q	0.153	0.135	0.138	0.123	<0.001	<0.001
UE_CE_q	0.058	0.031	-0.004	-0.004	<0.001	<0.001
$UE\_\Delta CE_{q,q+1}$	-0.122	-0.037	0.010	0.006	<0.001	<0.001
$\%SI_q$	3.85%	0.000	1.56%	0.000	<0.001	<0.001
$\Delta SALES_q$	0.110	0.062	0.150	0.092	<0.001	<0.001
$NEG\_\Delta SALES_q$	-0.052	0.000	-0.038	0.000	<0.001	<0.001
$NANALYS_{q+1}$	1.487	1.609	1.352	1.386	<0.001	<0.001
$JustMET_q$	0.153	0.000	0.160	0.000	0.065	0.035
$LOSS_q$	0.108	0.000	0.137	0.000	<0.001	<0.001
$REST_q$	0.194	0.000	0.090	0.000	<0.001	<0.001
$SIZE_{q+1}$	6.314	6.248	6.004	5.904	<0.001	<0.001

See Appendix for variable definitions. All variables except indicator variables are winsorized at 1st and 99th percentiles.

Table 3 reports the Spearman/Pearson correlations among the main variables used in the core earnings regression to classify classification shifters (Panel A) and for the variables used in the analyst forecast regressions (Panel B). The results indicate that analyst forecast revisions are negatively correlated with $SHIFT_q$, consistent with analysts discounting the earnings news for shifters. Still their forecasts are more positively biased for shifters, consistent with analyst failing to fully account for the unexpected lower future core earnings for shifters. Finally, the absolute value of analysts' forecast errors are positively related with $SHIFT_q$, suggesting that their forecast accuracy declines for shifters.

Table 3
Descriptive Statistics
Panel A: Spearman/Pearson Correlation Matrix for Relevant Variables Used to Classify Shifters

	CE_q	CE_{q-1}	CE_{q-4}	UE_CE_q	ΔCE_q	ΔCE_{q+1}	$UE\_\Delta CE_q$	$UE\_\Delta CE_{q+1}$	$\%SI_q$	ATO_q	ΔATO_q	$ACCR_{q-1}$	$ACCR_{q-4}$	$\Delta SALES_q$	NEG_ $\Delta SALES_q$	$RETURNS_q$	$RETURNS_{q-1}$
CE_q	1.000	0.753	0.663	0.420	0.324	-0.286	0.199	0.010	-0.185	-0.026	0.037	-0.259	-0.281	0.179	0.351	0.072	0.067
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0007)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
CE_{q-1}	0.823	1.000	0.653	0.016	-0.301	-0.073	-0.003	-0.009	-0.122	-0.037	0.010	-0.190	-0.325	0.118	0.277	0.053	0.067
	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.2569)	(0.0041)	(<.0001)	(<.0001)	(0.0005)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
CE_{q-4}	0.770	0.746	1.000	0.002	0.015	-0.102	-0.014	-0.007	-0.110	-0.045	0.010	-0.305	-0.224	-0.084	0.096	0.005	0.009
	(<.0001)	(<.0001)		(0.4687)	(<.0001)	(<.0001)	(<.0001)	(0.0197)	(<.0001)	(<.0001)	(0.0004)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.091)	(0.0022)
UE_CE_q	0.272	0.028	0.036	1.000	0.560	-0.276	0.451	0.057	-0.082	-0.009	0.026	-0.004	-0.008	0.011	0.015	-0.004	-0.002
	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.001)	(<.0001)	(0.1279)	(0.0027)	(<.0001)	(<.0001)	(0.1199)	(0.468)
$\Delta CE_{q-1,q}$	0.216	-0.221	0.023	0.462	1.000	-0.301	0.326	0.020	-0.099	0.016	0.043	-0.096	0.049	0.108	0.123	0.030	0.000
	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.9968)
$\Delta CE_{q,q+1}$	-0.214	-0.086	-0.115	-0.187	-0.227	1.000	-0.151	0.321	0.080	-0.015	-0.028	-0.026	-0.019	-0.052	-0.084	0.003	-0.016
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.3847)	(<.0001)
$UE\_\Delta CE_{q-1,q}$	0.187	0.031	0.017	0.646	0.313	-0.140	1.000	-0.034	-0.034	-0.007	-0.013	0.011	-0.003	0.003	-0.006	-0.006	-0.003
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(0.0165)	(<.0001)	(0.0002)	(0.3258)	(0.2946)	(0.0413)	(0.0321)	(0.2217)
$UE\_\Delta CE_{q,q+1}$	0.037	0.016	0.004	0.091	0.032	0.317	0.048	1.000	-0.004	-0.002	0.000	0.000	-0.003	-0.036	-0.047	-0.003	-0.001
	(<.0001)	(<.0001)	(0.1448)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(0.2343)	(0.4681)	(0.9098)	(0.8892)	(0.3602)	(<.0001)	(<.0001)	(0.3081)	(0.8332)
$\%SI_q$	-0.040	-0.017	-0.001	-0.022	-0.043	0.034	-0.020	-0.007	1.000	-0.047	-0.014	-0.011	-0.024	-0.070	-0.154	-0.078	-0.057
	(<.0001)	(<.0001)	(0.596)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0143)		(0.2343)	(0.4681)	(0.9098)	(0.8892)	(0.3602)	(<.0001)	(<.0001)	(0.3081)
ATO_q	-0.240	-0.262	-0.273	-0.036	0.041	-0.030	-0.024	-0.050	-0.070	1.000	0.400	0.075	0.065	0.019	0.067	0.029	0.027
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
ΔATO_q	0.133	-0.002	0.046	0.117	0.254	-0.103	0.057	-0.016	-0.007	0.151	1.000	-0.018	-0.014	0.010	0.025	0.031	0.022
	(<.0001)	(0.4547)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0085)	(<.0001)		(<.0001)	(<.0001)	(0.0005)	(<.0001)	(<.0001)	(<.0001)
$ACCR_{q-1}$	-0.334	-0.314	-0.358	-0.017	-0.024	-0.058	0.002	-0.031	-0.041	0.219	-0.061	1.000	0.352	0.066	0.087	0.007	0.026
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.3841)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(0.0118)	(<.0001)
$ACCR_{q-4}$	-0.351	-0.390	-0.328	-0.020	0.064	0.011	-0.008	-0.018	-0.084	0.195	-0.039	0.347	1.000	-0.025	-0.021	0.006	-0.015
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0003)	(0.0036)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(0.0242)	(<.0001)
$\Delta SALES_q$	0.250	0.207	0.067	-0.053	0.092	-0.047	-0.048	-0.073	-0.093	0.081	0.086	0.080	-0.020	1.000	0.568	0.066	0.086
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)
NEG_ $\Delta SALES_q$	0.274	0.232	0.106	-0.067	0.085	-0.055	-0.062	-0.077	-0.096	0.127	0.097	0.064	-0.030	0.843	1.000	0.059	0.073
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0022)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0003)	(<.0001)		(<.0001)	(<.0001)
$RETURNS_q$	0.117	0.103	0.038	-0.021	0.034	0.015	-0.020	-0.009	-0.053	0.057	0.076	-0.021	-0.010	0.102	0.103	1.000	0.007
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0014)	(0.0002)	(<.0001)	(<.0001)	(<.0001)	(0.2186)	(<.0001)	(<.0001)	(<.0001)		(0.0185)
$RETURNS_{q-1}$	0.116	0.114	0.046	-0.011	0.012	-0.018	-0.009	0.011	-0.043	0.059	0.057	0.003	-0.035	0.116	0.111	0.020	1.000
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0014)	(0.0002)	(<.0001)	(<.0001)	(<.0001)	(0.2186)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	

See Appendix for variable definitions. The full sample consists of 126,427 firm-quarter observations.The sample for analysts' forecasts has 70,306 firm-quarter observations.Spearman(Pearson) correlations are below(above) the diagonal. All variables except indicator variables are winsorized at 1st and 99th percentiles.

Table 3
Descriptive Statistics
Panel B: Spearman/Pearson Correlation Matrix for Variables Relevant for Analyst Forecast Regressions

	$FREV_q^{q+1}$	FE_q	FE_{q+1}	$\lvert FE_q \rvert$	$\lvert FE_{q+1} \rvert$	$SHIFT_q$	$\Delta EARN_q$	$JustMET_q$	$NANALYS_{q+1}$	$LOSS_q$	$REST_q$	$RESTCH_q$	$SIZE_q$	RETURNSq	RETURNSq-1
$FREV_q^{q+1}$	1.000	0.381	0.196	-0.290	-0.290	-0.013	0.209	0.052	0.089	-0.189	-0.057	0.109	0.121	0.152	0.080
		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
FE_q	0.362	1.000	0.301	-0.651	-0.349	0.026	0.358	0.069	0.139	-0.265	-0.003	0.062	0.153	0.111	0.090
	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.4524)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
FE_{q+1}	0.147	0.276	1.000	-0.287	-0.713	-0.046	0.091	0.043	0.139	-0.144	0.013	0.021	0.154	0.102	0.058
	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$\lvert FE_q \rvert$	-0.073	-0.031	-0.014	1.000	0.509	0.007	-0.179	-0.167	-0.231	0.269	0.061	-0.170	-0.283	-0.014	-0.105
	(<.0001)	(<.0001)	(0.0002)		(<.0001)	(0.0594)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0003)	(<.0001)
$\lvert FE_{q+1} \rvert$	-0.109	-0.103	-0.052	0.512	1.000	0.035	-0.093	-0.086	-0.221	0.213	0.037	-0.121	-0.261	-0.122	-0.092
	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$SHIFT_q$	-0.025	0.037	-0.044	0.015	0.023	1.000	0.006	-0.007	0.047	-0.028	0.110	-0.065	0.058	-0.022	-0.029
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(0.1417)	(0.0697)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$\Delta EARN_q$	0.212	0.314	0.089	-0.044	-0.061	0.004	1.000	0.026	-0.001	-0.098	-0.021	0.064	-0.007	0.107	0.122
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.3298)		(<.0001)	(0.8455)	(<.0001)	(<.0001)	(<.0001)	(0.0988)	(<.0001)	(<.0001)
$JustMET_q$	0.013	-0.018	-0.018	-0.579	-0.174	-0.007	0.021	1.000	0.063	-0.040	-0.025	0.025	0.026	0.005	0.006
	(0.0011)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0697)	(<.0001)		(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.2043)	(0.1366)
$NANALYS_{q+1}$	0.019	0.099	0.091	-0.334	-0.339	0.047	0.005	0.062	1.000	-0.129	0.110	-0.003	0.750	0.016	0.019
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.2036)	(<.0001)		(<.0001)	(<.0001)	(0.4148)	(<.0001)	(<.0001)	(<.0001)
$LOSS_q$	-0.096	-0.165	-0.073	0.195	0.184	-0.028	-0.097	-0.040	-0.130	1.000	0.011	-0.066	-0.159	-0.064	-0.061
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(0.0037)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
$REST_q$	-0.050	0.039	0.056	0.059	0.048	0.110	-0.038	-0.025	0.112	0.011	1.000	-0.565	0.158	0.006	0.006
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0037)		(<.0001)	(<.0001)	(0.1121)	(0.1214)
$RESTCH_q$	0.052	-0.034	-0.054	-0.065	-0.053	-0.110	0.047	0.027	-0.103	-0.016	-0.946	1	0.004	-0.006	0.040
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(0.3231)	(0.1317)	(<.0001)
$Size_{q+1}$	0.039	0.091	0.090	-0.388	-0.386	0.059	-0.006	0.025	0.759	-0.165	0.158	-0.145	1	-0.040	0.067
					(<.0001)	(<.0001)	(0.1744)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)		(<.0001)	(<.0001)
RETURNSq	0.161	0.160	0.093	-0.027	-0.118	-0.023	0.139	0.007	0.044	-0.078	0.002	0.002	0.012	1	0.034
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.0551)	(<.0001)	(<.0001)	(0.6076)	(0.5809)	(0.0021)		(<.0001)
RETURNSq-1	0.087	0.085	0.054	-0.107	-0.104	-0.030	0.148	0.006	0.046	-0.075	0.000	0.007	0.110	0.027	1
	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.1173)	(<.0001)	(<.0001)	(0.9454)	(0.0795)	(<.0001)	(<.0001)	

See Appendix for variable definitions. The full sample consists of 126,427 firm-quarter observations.The sample for analysts' forecasts has 70,306 firm-quarter observations.Spearman(Pearson) correlations are below(above) the diagonal. All variables except indicator variables are winsorized at 1st and 99th percentiles.

6. EMPIRICAL RESULTS

6.1 Regression Results for Core Earnings Model

Table 4 presents the mean regression results for the expected core earnings level model. As expected, prior quarter core earnings is a strong predictor of core earnings, with a mean coefficient of 0.544(0.330) for CE_{q-1} (CE_{q-4}), which is significant at less than 0.0001. Contrary to expectations, asset turnover ratio is positively correlated with core earnings. Last quarter accruals ($ACCR_{q-1}$) has a coefficient of -0.036, consistent with higher levels accruals having lower earnings persistence. Accruals of four quarters ago ($ACCR_{q-4}$) has a positive coefficient of 0.003, albeit on average not significant. Consistent with Anderson et al. (2003), the slope coefficient on sales growth ($\Delta SALES_q$) is significantly larger for firms that experience a decline in sales (0.023 vs. 0.427). The mean adjusted R^2 is high at 78.26%, ranging from 52.58% for Banks and 91.89% for Aerospace.

Table 5 reports the mean regression results for the expected core earnings change model using the quarterly data. The mean adjusted R^2 is 65.67%, which compares favorably to 51.7% for core earnings changes model using the annual data in McVay (2006). It ranges by industry from 30.17 for Banks to 85.39% for Books. Again all of the variables are statistically significant at the $p<0.10$ level with the predicted signs. Consistent with mean reversion, the level of core earnings is negatively correlated with the change in core earnings (Freeman et al. 1982). The change in core earnings from prior quarters (ΔCE_{q-1} and $\Delta CE_{q-4)}$ is negatively correlated with change in core earnings in current quarter, consistent with Brooks and Buckmaster (1976). The change in assets turnover ratio is not significant in the mean regression, even though the sign is consistent with Penman and Zhang (2002). For the majority (52%) of the 2,483 industry-quarter regressions, the variable is not significant.

Table 4
Expected Core Earnings Level Model

Dependent Variable : CE_q					
Independent Variables	Predicted Sign	Mean Coefficient	One-tailed p-value	Percent Significant (p-value<=0.10)	Percent with Sign in the Predicted Direction
Intercept		0.015	<.0001		
CE_{q-1}	+	0.544	<.0001	80.10	92.3
CE_{q-4}	+	0.330	<.0001	72.94	89.2
ATO_q	-	0.003	0.008	83.25	47.0
$ACCR_{q-1}$	-	-0.036	<.0001	56.34	63.7
$ACCR_{q-4}$	-	0.003	0.2646	60.85	52.3
$\Delta SALES_q$	+	0.023	0.0027	65.81	63.4
$NEG\_\Delta SALES_q$	+	0.404	<.0001	47.97	74.3
$RETURNS_q$	+	0.021	<.0001	68.91	63.1
$RETURNS_{q-1}$	+	0.021	<.0001	71.33	57.1
Adjusted R^2		78.76%			

See Appendix for variable definitions. There are 126,427 firm-quarter observations and 2,483 industry-quarter regressions for the 1990 to 2010 period. The regressions are estimated cross-sectionally by industry and fiscal year following (1) below based on Fan et al.(2010). p-values, rather than t-statistics, are provided due to the different sample size of the specific regressions, which range from 15 to 439 observations. The overal adjusted R^2 is 78.32%, ranging by industry from 52.58% for Banks to 91.89% for Aerospace. All variables are winsorized at 1st and 99th percentiles.

$$CE_q = \beta_0+\beta_1 CE_{q-1} +\beta_2 CE_{q-4} +\beta_3 ATO_q +\beta_4 ACCR_{q-1}+\beta_5 ACCR_{q-4} +\beta_6 \Delta SALES_q +\beta_7 NEG\_\Delta SALES_q +\beta_8 RETURNS_q+\beta_9 RETURNS_{q-1}+\varepsilon_q \quad (1)$$

6.2 Regression Results for Analysts' Forecasts

6.2.1 Analyst Forecast Revision

Table 6 presents the results of Model (5) that examine the effect of classification shifting on next quarter forecast revisions. All of the coefficients are significant with the predicted sign. To control for cross-sectional dependence and heteroskedastic and autocorrelated residuals, t-statistics based on robust standard errors clustered by year and firm are reported (Peterson 2007; Gow et al, 2010). The coefficient on $SHIFT_{i,q}$ is negative and significant at the 0.001 level, suggesting that analysts revise their next quarter forecasts downward for shifters. Perhaps more

Table 5
Expected Core Earnings Changes Model

Dependent Variable : ΔCE_q

Independent Variables	Predicted Sign	Mean Coefficient	One-tailed p-value	Percent Significant (p-value<=0.10)	Percent with Sign in the Predicted Direction
Intercept		0.023	0.0333		
CE_{q-1}	-	-0.638	<.0001	75.51	86.75
ΔCE_{q-1}	-	-0.220	0.0087	54.73	57.35
CE_{q-4}	+	0.450	<.0001	68.87	84.58
ΔCE_{q-4}	-	-0.115	0.0005	55.86	62.79
ΔATO_q	+	0.001	0.8789	78.41	62.26
$ACCR_{q-1}$	-	-0.034	0.1847	56.22	60.57
$ACCR_{q-4}$	+	-0.007	0.5955	61.26	50.22
$\Delta SALES_q$	+	0.027	0.1019	65.97	61.30
$NEG\_\Delta SALES_q$	+	0.417	0.0042	50.42	69.83
$RETURNS_q$	+	0.030	0.0399	69.47	62.51
$RETURNS_{q-1}$	+	0.038	0.0563	69.51	56.99
Adjusted R^2		65.67%			

See Appendix for variable definitions. There are 126,427 firm-quarter observations and 2,483 industry-quarter regressions for the 1990 to 2010 period. The regressions are estimated cross-sectionally by industry and fiscal year following (2) below. p-values, rather than t-statistics, are provided due to the different sample size of the specific regressions, which range from 15 to 439 observations. The overal adjusted R^2 is 62.33%, ranging by industry from 30.17% for Banks to 85.39% for Books. All variables are winsorized at 1st and 99th percentiles.

$$\Delta CE_q = \delta_0+\delta_1 CE_{q-1} +\delta_2\Delta CE_{q-1}+\delta_3 CE_{q-4} +\delta_4\Delta CE_{q-4} +\delta_5\Delta ATO_q +\delta_6 ACCR_{q-1}+\delta_7 ACCR_{q-4} +\delta_8\Delta SALES_q +\delta_9 NEG\_\Delta SALES_q +\delta_{10} RETURNS_q+\delta_{11} RETURNS_{q-1}+\nu_q \quad (2)$$

telling is the significantly negative coefficient of the interaction term of forecast error $FE_{i,q}$ and $SHIFT_{i,q}$. In fact, the analyst forecast revision for the earnings news for shifters (0.031) is only half as much it is for nonshifters (0.062). This result indicates that analysts believe the core earnings news for shifters are significantly less persistent for shifters than for non-shifters, consistent with H1.

As expected, the coefficient on earnings surprise $FE_{i,q}$ is positive and significant at the 0.001 level, suggesting that analyst adjust their earnings forecasts in response to earnings surprise. Analysts also revise their earnings forecasts upward for firms that just meet or beat

Table 6
Results of Analysts' Forecast Revision Regressions

$$FREV_{i,q+1}=\gamma_0+\gamma_1 FE_{i,q}+\gamma_2 SHIFT_{i,q}+\gamma_3 FE_{i,q}*SHIFT_{i,q}++\gamma_4 JustMET_{i,q}+\gamma_5 LOSS_{i,q}+\gamma_6 REST_{i,q}+e_{i,q+1}$$

Independent Variables	Predicted Sign	Estimated Coefficient	Cluster Robust t-Statistics	p-value
Intercept		-0.001	-3.389	<0.001
SURP	+	0.062	9.220	<0.001
SHIFT	-	-0.001	-5.424	<0.001
SURP*SHIFT	-	-0.031	-3.175	0.002
JustMET	+	0.000	3.540	<0.001
LOSS	-	-0.003	-5.692	<0.001
REST	-	-0.002	-4.743	<0.001
INDUSTRY EFFECTS		YES		
Number of Observations		70,306		
Adjusted R^2		7.25%		

See Appencix for variable definitions. t-statistics are based on robust standard errors clustered by firm and year. All variables except indicator variables are winsorized at 1st and 99th percentile.

earnings forecasts, as indicated by the significantly positive but relatively small coefficient on the dummy variable JustMET. This result is opposite to the finding in Kaznik and McNichol (2002), where analysts do not reward firms meeting or beating forecast with higher future earnings forecasts. Consistent with prior studies, the coefficient on the dummy variable for LOSS is negative, suggesting that analysts revise their next quarter ahead forecasts downward for firms suffering from a loss. The coefficient on the dummy variable for restructuring REST is also negative, consistent with prior evidence that analysts believe firms with restructuring charge tend to have decrease in earnings (Chaney et al. 1999).

6.2.2 Analyst Forecast Bias and Accuracy

Table 7 and 8 report the results of Models (6) and (7) which examine the effects of classification shifting on analyst forecast bias and accuracy. In Table 7, the coefficient on SHIFT is negative and significant at the 0.001 level. The negative coefficient suggests that analysts are more optimistically biased for shifters than for non-shifters. This result, combined with our earlier result on forecast revision, indicates that even though analysts may respond less to the earnings news for shifters, they cannot accurately assess the full extent of the inflated core earnings that will reverse in the next period, which lead to their overestimates shifters' next quarter core earnings.

Consistent with expectation, the coefficient on lagged forecast error is positive and significant at the 0.01 level. The coefficients on ACCR and REST are non-significant. Contrary to expectation, the coefficient on SI is positive but insignificant. The coefficients on both prior and current market returns are positive and significant, suggesting that analysts do not reflect all information impounded in past stock returns for future earnings. The coefficients on both analyst following and firm size are positive and significant, meaning that analyst forecasts are less biased upward with greater following and for larger firms. The adjusted R^2 for this regression is 6.09%.

In Table 8, the coefficient on SHIFT is positive and significant at the 0.001 level. The positive coefficient indicates that analysts forecasts are less accurate for classification shifters than for non-shifters. This reflects the fact that firms that manipulate their earnings through classification shifting make it more difficult for analysts to forecast their earnings accurately.

The coefficient on lagged forecast error is positive and significant. The coefficient on ACCR is not significantly different from zero. Consistent with prior study, the coefficient on REST is positive and significant, suggestion that forecast accuracy is lower for firms that report a restructuring charge (Chaney et al. 1999). The variable SI is not significantly different from zero. The coefficient on analyst following is negative but not significant. Finally, the coefficient on firm size is negative and significant, consistent with larger firms having better information environment that makes analyst forecasts more accurate. The adjusted R^2 for this regression is 9.27%.

Table 7
Results of Analysts' Forecast Bias Regressions

$$FE_{i,q+1}=\lambda_0+\lambda_1 FE_{i,q}+\lambda_2 SHIFT_{i,q}+\lambda_3 ACCR_{i,q}+\lambda_4 REST_{i,q}+\lambda_5 SI_{i,q}+\lambda_6 RET_{i,q}+\lambda_7 RET_{i,q+1}+\lambda_8 NANALYS_{i,q+1}+\lambda_9 SIZE_{i,q+1}+\mu_{i,q+1}$$

Independent Variables	Predicted Sign	Estimated Coefficient	Cluster Robust t-Statistics	p-value
Intercept		-0.024	-4.075	<0.001
$FE_{i,q}$	+	0.190	2.619	0.004
$SHIFT_{i,q}$	-	-0.007	-3.181	0.002
$ACCR_{i,q}$	-	-0.001	-1.218	0.112
$REST_{i,q}$	-	-0.001	-0.743	0.229
$SI_{i,q}$	-	0.012	0.425	0.335
$RET_{i,q}$	?	0.015	4.207	<0.001
$RET_{i,q+1}$	?	0.026	3.452	<0.001
$NANALYS_{i,q+1}$	+	0.002	1.608	0.054
$SIZE_{i,q+1}$	+	0.003	3.123	<0.001
INDUSTRY EFFECTS		YES		
Number of Observations		70,306		
Adjusted R^2		6.09%		

See Appendix for variable definitions. t-statistics are based on robust standard errors clustered by firm and year. All variables except indicator variables are winsorized at 1st and 99th percentile.

Table 8
Results of Analysts' Forecast Accuracy Regressions

$$|FE_{i,q+1}|=\alpha_0+\alpha_1|FE_{i,q}|+\alpha_2 SHIFT_{i,q}+\alpha_3 ACCR_{i,q}+\alpha_4 REST_{i,q}+\alpha_5 SI_{i,q}+\alpha_6 RET_{i,q}+\alpha_7 RET_{i,q+1}+\alpha_8 NANALYS_{i,q+1}+\alpha_9 SIZE_{i,q+1}+\xi_{i,q+1}$$

Independent Variables	Predicted Sign	Estimated Coefficient	Cluster Robust t-Statistics	p-value
Intercept		0.038	5.323	<0.001
$\lvert FE_{i,q}\rvert$	+	0.367	7.456	<0.001
$SHIFT_{i,q}$	+	0.006	3.179	<0.001
$ACCR_{i,q}$	+	0.000	0.556	0.289
$REST_{i,q}$	+	0.008	3.572	<0.001
$SI_{i,q}$	+	0.018	0.674	0.250
$RET_{i,q}$	?	-0.029	-5.787	<0.001
$RET_{i,q+1}$	?	-0.010	-1.488	0.932
$NANALYS_{i,q+1}$	-	-0.001	-1.230	0.109
$SIZE_{i,q+1}$	-	-0.005	-4.638	<0.001
INDUSTRY EFFECTS		YES		
Number of Observations		70,306		
Adjusted R^2		9.27%		

See Appendix for variable definitions. t-statistics are based on robust standard errors clustered by firm and year. All variables except indicator variables are winsorized at 1st and 99th percentile.

7. ADDITIONAL ANALYSES

I ran additional analyses to make sure that the results are robust. Specifically, I excluded shifting firms that reported restructuring charges, that shifted in the prior quarter q-1, and that shifted in the next quarter q+1. I also restricted my sample to those with December fiscal year end or to the post-SOX era of 2002. Finally, I reran the analysis using the annual data. The following section reports the results of these additional tests.

7.1 Removing Shifters with Restructuring Charges

Previous research has documented that analyst forecast is less accurate and more optimistic for firms with restructuring charges (Chaney et al. 1996; Hanna and Orpurt 2006). As restructuring charges is a common type of special items and shifting firms are typically special item firms, my analyst forecast results could simply be driven by firms reporting restructuring charges. To examine whether the evidence that I document is due to this alternative explanation, I remove shifters with restructuring charges. As presented in Table 9, the results remain qualitatively the same, suggesting that the impact of classification shifting on analyst forecast is distinct from that of restructuring charges.

7.2 Removing Firms Shifting in t-1 or t+1

It is possible that firms could shift in the year prior to t that is under study. If this is the case, then the task of forecasting will be more complex. As a result, my finding may contain greater noise. Therefore, I remove firms that also shift in the previous year or in the year after and report the results in Table 10 and Table 11, respectively. Again the inferences remain essentially the same, suggesting that my findings are not significantly affected by firms that continuously shift.

Table 9
Regression Results after Removing Shifters with Restructuring Charges

Independent Variables	Estimated Coefficients		
	DV=$FREV_{i,t+1}$	DV=$FE_{i,t+1}$	DV=$\|FE_{i,t+1}\|$
Intercept	-0.002	-0.024	0.038
	(-3.464)	(-3.996)	(5.224)
$FE_{i,t}$	0.071	0.200	
	(-8.780)	(2.931)	
$\|FE_{i,t}\|$			0.363
			(6.775)
$SHIFT_{i,t}$	-0.001	-0.008	0.006
	(-4.172)	(-3.128)	(2.984)
$FE_{i,t}$*$SHIFT_{i,t}$	-0.027		
	(-2.205)		
$ACCR_{i,t}$		-0.001	0.000
		(-1.433)	(0.536)
$JUSTMET_{i,t}$	0.001		
	(3.343)		
$LOSS_{i,t}$	-0.003		
	(-6.908)		
$REST_{i,t}$	-0.002	-0.003	0.009
	(-5.712)	(-1.488)	(3.273)
$SI_{i,t}$		0.013	0.020
		(0.481)	(0.690)
$Ret_{i,t}$		0.016	-0.027
		(3.961)	(-5.946)
$Ret_{i,t+1}$		0.026	-0.010
		(3.443)	(-1.522)
$NANALYS_{i,t+1}$		0.002	-0.001
		(1.436)	(-1.234)
$SIZE_{i,t+1}$		0.003	-0.005
		(3.059)	(-4.526)
INDUSTRY EFFECTS	YES	YES	YES
Number of Observations	67,231	67,231	67,231
Adjusted R^2	7.32%	6.38%	9.36%

See Appendix for variable definitions. t-statistics are based on robust standard errors clustered by firm and year. All variables except indicator variables are winsorized at 1st and 99th percentile.

Table 10
Regression Results after Removing Firms Shifting in t-1

Independent Variables	Estimated Coefficients DV=$FREV_{i,t+1}$	DV=$FE_{i,t+1}$	DV=$\|FE_{i,t+1}\|$
Intercept	-0.002	-0.024	0.038
	(-3.667)	(-4.059)	(5.275)
$FE_{i,t}$	0.071	0.191	
	(8.808)	(2.597)	
$\|FE_{i,t}\|$			0.367
			(7.341)
$SHIFT_{i,t}$	-0.001	-0.007	0.007
	(-4.363)	(-3.286)	(3.077)
$FE_{i,t}$*$SHIFT_{i,t}$	-0.027		
	(-2.671)		
$ACCR_{i,t}$		-0.001	0.000
		(-1.201)	(0.555)
$JUSTMET_{i,t}$	0.001		
	(3.311)		
$LOSS_{i,t}$	-0.003		
	(-6.876)		
$REST_{i,t}$	-0.002	-0.001	0.008
	(-5.775)	(-0.658)	(3.589)
$SI_{i,t}$		0.010	0.018
		(0.378)	(0.660)
$Ret_{i,t}$		0.015	-0.029
		(4.190)	(-5.737)
$Ret_{i,t+1}$		0.027	-0.010
		(3.452)	(-1.535)
$NANALYS_{i,t+1}$		0.002	-0.001
		(1.563)	(-1.240)
$SIZE_{i,t+1}$		0.003	-0.005
		(3.128)	(-4.582)
INDUSTRY EFFECTS	YES	YES	YES
Number of Observations	69,694	69,694	69,694
Adjusted R^2	7.24%	6.08%	9.26%

See Appendix for variable definitions. t-statistics are based on robust standard errors clustered by firm and year. All variables except indicator variables are winsorized at 1st and 99th percentile.

Table 11
Regression Results after Removing Firms Shifting in t+1

Independent Variables	DV=$FREV_{i,t+1}$	DV=$FE_{i,t+1}$	DV=$\|FE_{i,t+1}\|$
	Estimated Coefficients		
Intercept	0.000	-0.024	0.038
	(-3.868)	(-4.043)	(5.300)
$FE_{i,t}$	0.000	0.191	
	(8.790)	(2.619)	
$\|FE_{i,t}\|$			0.368
			(7.444)
$SHIFT_{i,t}$	0.008	-0.007	0.006
	(-4.136)	(-3.086)	(3.379)
$FE_{i,t}$*$SHIFT_{i,t}$	0.143		
	(-2.274)		
$ACCR_{i,t}$		-0.001	0.001
		(-1.582)	(0.757)
$JUSTMET_{i,t}$	0.002		
	(3.335)		
$LOSS_{i,t}$	0.021		
	(-6.822)		
$REST_{i,t}$	0.006	-0.001	0.008
	(-5.657)	(-0.771)	(3.597)
$SI_{i,t}$		0.010	0.018
		(0.364)	(0.672)
$Ret_{i,t}$		0.015	-0.028
		(4.389)	(-5.838)
$Ret_{i,t+1}$		0.027	-0.010
		(3.348)	(-1.515)
$NANALYS_{i,t+1}$		0.002	-0.001
		(1.443)	(-1.126)
$SIZE_{i,t+1}$		0.003	-0.005
		(3.097)	(-4.606)
INDUSTRY EFFECTS	YES	YES	YES
Number of Observations	69,694	69,694	69,694
Adjusted R^2	7.04%	6.07%	9.33%

See Appendix for variable definitions. t-statistics are based on robust standard errors clustered by firm and year. All variables except indicator variables are winsorized at 1st and 99th percentile.

7.3 Subsample of Post-SOX Period

There is evidence that Sarbanes-Oxley Act of 2002 has a significant impact on financial reporting behavior in general and earnings management in particular. It appears that accruals management is gradually replaced by other earnings management techniques including real earnings management and classification shifting (McVay 2006; Cohen et al. 2008; Kolev et al. 2008). To explore whether my results hold during this period, I restrict my sample to the post-SOX time frame. In Table 12, we can see that all major results remain essentially the same.

Table 12
Regression Results using Quarterly Data Post-SOX

Independent Variables	Estimated Coefficients		
	DV=$FREV_{i,t+1}$	DV=$FE_{i,t+1}$	DV=$\|FE_{i,t+1}\|$
Intercept	-0.024	-0.032	0.054
	(-2.934)	(-3.698)	(4.954)
$FE_{i,t}$	0.402	0.181	
	(2.809)	(1.722)	
$\|FE_{i,t}\|$			0.329
			(4.404)
$SHIFT_{i,t}$	-0.009	-0.008	0.007
	(-3.864)	(-2.683)	(2.601)
$FE_{i,t}$*$SHIFT_{i,t}$	-0.303		
	(-2.024)		
$ACCR_{i,t}$		0.000	0.000
		(-0.569)	(0.422)
$JUSTMET_{i,t}$	-0.002		
	(-0.873)		
$LOSS_{i,t}$	0.029		
	(1.357)		
$REST_{i,t}$	-0.011	0.000	0.006
	(-1.975)	(0.024)	(4.071)
$SI_{i,t}$		0.001	0.005
		(0.026)	(0.344)
$Ret_{i,t}$		0.014	-0.031
		(3.105)	(-6.058)
$Ret_{i,t+1}$		0.031	-0.018
		(3.587)	(-1.845)
$NANALYS_{i,t+1}$		0.001	-0.001
		(0.823)	(-0.758)
$SIZE_{i,t+1}$		0.004	-0.006
		(3.265)	(-4.412)
INDUSTRY EFFECTS	YES	YES	YES
Number of Observations	32,905	32,905	32,905
Adjusted R^2	6.07%	4.24%	8.73%

See Appendix for variable definitions. t-statistics are based on robust standard errors clustered by firm and year. All variables except indicator variables are winsorized at 1st and 99th percentile.

7.4 Subsample of December Fiscal Year End Only

As my sample consists of firm quarterly data with different fiscal year end, there may exist greater variation in the information set available. To increase comparability and to reduce noise, I also analyze a subsample consisting of firms with December fiscal year end only. The results in Table 13 indicate that my results are not sensitive to this data restriction.

Table 13
Regression Results using Quarterly Data with December Fiscal Year End Only

Independent Variables	Estimated Coefficients		
	$DV=FREV_{i,t+1}$	$DV=FE_{i,t+1}$	$DV=\|FE_{i,t+1}\|$
Intercept	-0.024	-0.032	0.046
	(-2.934)	(-3.698)	(4.954)
$FE_{i,t}$	0.402	0.181	
	(2.809)	(1.722)	
$\|FE_{i,t}\|$			0.329
			(4.404)
$SHIFT_{i,t}$	-0.009	-0.008	0.008
	(-3.864)	(-2.683)	(2.601)
$FE_{i,t}*SHIFT_{i,t}$	-0.303		
	(-2.024)		
$ACCR_{i,t}$		0.000	0.000
		(-0.569)	(0.422)
$JUSTMET_{i,t}$	-0.002		
	(-0.873)		
$LOSS_{i,t}$	0.029		
	(1.357)		
$REST_{i,t}$	-0.011	0.000	0.009
	(-1.975)	(0.024)	(4.071)
$SI_{i,t}$		0.001	0.012
		(0.026)	(0.344)
$Ret_{i,t}$		0.014	-0.031
		(3.105)	(-6.058)
$Ret_{i,t+1}$		0.031	-0.018
		(3.587)	(-1.845)
$NANALYS_{i,t+1}$		0.001	-0.001
		(0.823)	(-0.758)
$SIZE_{i,t+1}$		0.004	-0.006
		(3.265)	(-4.412)
INDUSTRY EFFECTS	YES	YES	YES
Number of Observations	45,304	45,304	45,304
Adjusted R^2	5.67%	4.17%	8.13%

See Appendix for variable definitions. t-statistics are based on robust standard errors clustered by firm and year. All variables except indicator variables are winsorized at 1st and 99th percentile.

7.5 Using Annual Data

Finally, I also reran the analyses using annual data. Again, I find results consistent with using quarterly data.

Table 14
Regression Results using Annual Data

Independent Variables	Estimated Coefficients		
	DV=$FREV_{i,t+1}$	DV=$FE_{i,t+1}$	DV=$\|FE_{i,t+1}\|$
Intercept	-0.067	-0.543	0.061
	(-1.708)	(-2.389)	(2.041)
$FE_{i,t}$	0.158	0.507	
	(9.964)	(1.329)	
$\|FE_{i,t}\|$			0.040
			(1.811)
$SHIFT_{i,t}$	-0.010	-0.112	0.013
	(-2.9143)	(-2.039)	(2.326)
$FE_{i,t}$*$SHIFT_{i,t}$	-0.003		
	(-2.262)		
$ACCR_{i,t}$		0.032	0.112
		(1.910)	(1.508)
$JUSTMET_{i,t}$	0.010		
	(1.368)		
$LOSS_{i,t}$	-0.025		
	(-3.190)		
$REST_{i,t}$	-0.013	0.034	0.007
	(-1.739)	(1.692)	(1.140)
$SI_{i,t}$		-0.014	0.019
		(-1.531)	(1.956)
$Ret_{i,t}$		0.002	-0.071
		(2.682)	(-2.021)
$Ret_{i,t+1}$		0.003	-0.019
		(2.443)	(-1.226)
$NANALYS_{i,t+1}$		-0.003	-0.001
		(-1.434)	(-1.126)
$SIZE_{i,t+1}$		-0.041	-0.005
		(-3.601)	(-4.606)
INDUSTRY EFFECTS	YES	YES	YES
Number of Observations	24,101	24,101	24,101
Adjusted R^2	7.25%	6.34%	6.33%

See Appendix for variable definitions. t-statistics are based on robust standard errors clustered by firm and year. All variables except indicator variables are winsorized at 1st and 99th percentile.

8. CONCLUSIONS

Prior literature has documented large sample evidence of income classification shifting. However, there is relatively little evidence of its impact on market participants. As investors and analysts tend to focus on core earnings (Bradshaw and Sloan 2002; Gu and Chen 2004), the artificially inflated core earnings reported by income classification shifters could have significant impact on market's accurate processing of earning information.

Drawing on core earnings level and changes model from McVay (2006) and Fan et al. (2010), I am able to classify firms into likely shifters and non-shifters and examine how income classification shifting affects analysts' forecasts. I find that analyst forecast revision is significantly less for earnings news by shifters, implying that analysts recognize that the opportunistically boosted core earnings by shifters are less likely to persist into the future. However, analysts cannot fully assess the extent of the implications of income shifting on future earnings, leading to more optimistically biased forecast for shifters. Finally, such earnings manipulation also makes it more difficult for analysts to forecast income classification shifters' earnings accurately.

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APPENDIX
Variable Definitions

Variable	Definition
CE_q	= Core Earnings, calculated as Sales(saleq) - Cost of Goods Sold(cogsq) - Selling, General, and Administrative Expenses (xsgaq) in quarter q scaled by Sales (saleq)
$\Delta CE_{q,q+1}$	= Change in Core Earnings, calculatd as CE_{q+1} - CE_q
UE_CE_q	= Unexpected Core Earnings, calculated as the difference between the reported and predicted core earnings(CEq), estimated from the follwing model by industry-year-quarter, excluding firm i: $CE_q = \beta_0+\beta_1 CE_{q-1} +\beta_2 CE_{q-4} +\beta_3 ATO_q +\beta_4 ACCR_{q-1}+\beta_5 ACCR_{q-4} +\beta_6 \Delta SALES_q +\beta_7 NEG\_\Delta SALES_q + \beta_8 RETURNS_q+\beta_9 RETURNS_{q-1}+\varepsilon_q$
$UE\_\Delta CE_q$	= Unexpected Change in Core Earnings in quarter q+1, calculated as the difference between the reported and predicted change in core earnings (ΔCEq), estimated from the follwing model by industry-year-quarter, excluding firm i: $\Delta CE_q = \delta_0+\delta_1 CE_{q-1} +\delta_2 \Delta CE_{q-1}+\delta_3 CE_{q-4} +\delta_4 \Delta CE_{q-4} +\delta_5 ATO_q +\delta_6 ACCR_{q-1}+\delta_7 ACCR_{q-4} +\delta_8 \Delta SALES_q+\delta_9 NEG\_\Delta SALES_q +\delta_{10} RETURNS_q+\delta_{11} RETURNS_{q-1}+\nu_q$
$\%SI_q$	= Special Items(spiq) as a percentage of sales(saleq). Income-decreasing special items are multiplied by -1, and are set to 0 where special items are income-increasing.
ATO_q	= Asset Turnover Ratio, calculated as $Sales_q/((NOA_q+NOA_{q-1})/2)$, where NOA_q, or net operating assets, is opearting assets minus opearting liabilities. Opearing assets are calculated as total assets(atq) less cash and short-term investoments(cheq). Operating liabilities is calculated as total assets(atq) less total debt(dlcq and dlttq), less book avlue of common and preffered equity(pstkq and cstkq), less mnority interst(mibq). Average NOA is required to be positive.
ΔCATOq,q-1	Change in Asset Turnover, calculated as ATO_q-ATO_{q-1}.
$ACCR_q$	= Operating Accruals, calculated as net income before extraordinary items(ibq) minus cash from operations(oancfy), scaled by $Sales_q$.
$\Delta SALES_q$	= Percentage Change in Sales, calculated as $(SALES_q-SALES_{q-4})/SALES_{q-4}$
$NEG\_\Delta SALES_q$	= $\Delta SALES_q$ if the percentage change in sales is less than 0, and 0 otherwise.
$RETURNS_q$	= Three-month market-adjusted value weighted return exclusive of dividends corresponding to the fiscal quarter
$FREV_q^{q+1}$	= Analyst Forecast Revision, calculated as the difference between the first analyst mean forecast for quarter q+1 after the earnings announcement in quarter q and the last analyst mean forecast for quarter q+1 before earnings announcement in quarter q, scaled by beginning of period stock price
FE_q	= Forecast Error, calculated as the difference between I/B/E/S actual EPS and the last analyst mean forecast for quarter q, scaled by beginning of period stock price
$\|FE_q\|$	= Forecast Accuracy, calculated as the absoluate value of analyst forecast error for quarter q, FE_q, scaled by beginning of preiod stock price
$SHIFT_q$	= 1 if the firm has positive unexpected core earnings and negative special items in quarter q and negative unexpected change in core earnings in quarter q+1
JustMET	= 1 if the firm reported an earnings forecast error equal to $0.00 or $0.01
$NANALYS_q$	= Log of the number of analysts forecasts included in the I/B/E/S mean forecast for quarter q
$LOSS_q$	= 1 if operating income before depreciation(oibdpq) in quarter t is less than zero, 0 otherwise
$REST_q$	= 1 if the firm reported a restructuring charge in quarter q, 0 otherwise
$RESTCH_q$	= Restructuring charge per share in quarter q deflated by price per share at the beginning of quarter q
$Size_q$	= Log of the total market value of firm i at the beginning of quarter q

VITA

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