Accrual Reversals, Earnings and Stock Returns

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Abstract

Accounting accruals anticipate future economic benefits. They are intended to reverse upon the realization of the anticipated future benefits, such that their reversals have no net impact on future earnings. In practice, however, we show that extreme accruals exhibit a high frequency of subsequent reversals that do impact future earnings. We demonstrate that these reversals explain a number of previously documented results, including the low persistence of accruals and the negative relations between accruals and both future earnings changes and future stock returns. We also corroborate our findings using a hand-collected sample of inventory write-downs, demonstrating that extreme positive inventory accruals are followed by a disproportionately high frequency and magnitude of subsequent inventory write-downs. Our results suggest that extreme accruals contain a significant amount of estimation error that has predictable consequences for future accruals, earnings and stock returns.

1. Introduction

The accrual process is an important feature of financial accounting. Yet there is limited research documenting and explaining the properties of accruals.[1] In this study, we seek to contribute to research in this area by documenting and explaining some fundamental properties of accounting accruals and describing their implications for accounting research and practice.

Accrual accounting involves the anticipation of probable future economic benefits (e.g., future cash inflows) and obligations (e.g., future cash outflows). In doing so, it allows the financial effects of current transactions and events to be recognized in the current period rather than when the associated benefits are realized. Accruals should reverse when their anticipated benefits are realized, such that their reversals should have no net impact on subsequent earnings. Since accruals are just estimates of anticipated future benefits, subsequent realizations may differ from these estimates. In such cases, the accrual must still reverse and the difference between the anticipated and realized benefit run through earnings. For example, if the net realizable value of inventory falls below its original cost, an inventory write down is required in the amount of the difference.

If accruals are unbiased estimates of future benefits, then accrual estimation errors and their associated reversals should be unpredictable. We show that observed accruals fail this test at a basic level. Specifically, we demonstrate that extreme accruals exhibit a disproportionately high frequency of subsequent reversals and that these reversals impact future earnings. For example, we show that extreme positive inventory accruals are followed by a disproportionately high frequency and magnitude of subsequent inventory write-downs. We also demonstrate that the prevalence of extreme accrual reversals explains a number of results from previous research:

[1] See Dechow, Ge and Schrand (2010) for a recent review of research in this area.

(i) **Accruals are strongly mean reverting, while earnings and cash flows are more slowly mean reverting.** We show that very few accruals actually revert toward the mean. Instead, extreme accruals tend be either highly persistent, or reverse to the opposite extreme. The combination of high a frequency both extremely persistent and extremely reversing accruals creates the false impression that accruals are strongly mean reverting.

(ii) **Accruals are negatively related to future earnings changes and stock returns.** We show that the negative relations between accruals and both future earnings changes and future stock returns are attributable to the high frequency of accrual reversals. After controlling for accrual reversals, the negative relations disappear.

Our findings make several contributions to the existing literature. First and foremost, we document the systematic reversal of estimation errors in extreme accruals and link them to the previous literature on the relations between accruals, earnings and stock returns. Estimation errors in extreme accruals are pervasive and we show that they have an economically and statistically significant impact on earnings and stock returns. We note that there are several non-mutually exclusive explanations for the prevalence of systematic estimation errors in extreme accruals. These include intentional earnings management, overinvestment, delayed accounting responses to economic shocks and GAAP-induced accounting distortions. We discuss these explanations in more detail in section 6. Our primary purpose in this paper is to document the economic significance and impact of such errors.

Second, we show that the reversal of estimation errors in extreme accruals explains the "accrual anomaly". A number of recent papers have provided non-accounting explanations for this anomaly (e.g., Fairfield et al. 2003; Kahn 2007; Zhang 2007; Wu, Zhang and Zhang 2010).

These papers argue that accruals are correlated with economic characteristic and that it is these other economic characteristics that predict future stock returns. In contrast, we identify extreme accrual reversals as the driver of the accrual anomaly. We also use our hand-collected sample of inventory write-downs to illustrate the process through which extreme accrual estimation errors reverse and cause predictable earnings changes.

Third, our analysis provides an explanation for the particularly strong relation between inventory accruals and future stock returns documented in Thomas and Zhang (2002). Thomas and Zhang show that inventory accruals are strongly mean reverting, but do not provide an explanation as to why. We demonstrate that this result arises because extreme positive inventory accruals contain a particularly high proportion of extreme reversals. We also show that these reversals frequently manifest themselves as large inventory write-downs.

Our paper is organized as follows. Section 2 provides an overview of previous research and develops our empirical predictions. Section 3 describes our data, section 4 presents our large sample accrual analysis and section 5 presents our detailed inventory write-down analysis. Section 6 provides concluding remarks.

2. Literature Review and Hypothesis Development

2.1 Literature Review

Accrual reversals are considered in a number of previous studies. One of the earliest studies is Defond and Park (2001). They model normal working capital accruals as a function of sales growth and show that the remaining 'abnormal' accruals are less persistent and that stock prices and analysts' earnings forecasts at least partially anticipate the lower persistence of abnormal accruals. Their results are consistent with abnormal accruals containing more estimation errors and hence resulting in a greater frequency of subsequent reversals, though they provide no direct evidence of accrual reversals.

Subsequent research by Dechow and Dichev (2002) measures accrual ‘estimation errors’ as residuals from regressions of accruals on past, present and future cash flows. They show that firms with extreme accrual estimation errors tend to have extreme accruals and low earnings persistence. Thus, their evidence is consistent with extreme accruals containing a disproportionately high frequency of extreme accrual estimation errors and with these estimation errors causing lower earnings persistence. They do not, however, provide direct evidence on the reversal of accrual estimation errors or their role in explaining the predictable earnings changes and stock returns following extreme accruals.

Moehrle (2002) examines the reversal of restructuring liability accruals. His evidence suggests that firms initially record excessively large restructuring liabilities and then strategically reverse the liabilities in future periods to meet earnings targets. Moehrle does not document the magnitude of the associated reversals or their impact on earnings and stock returns, since his hypotheses relate solely to the timing of the reversals.

Chan et al. (2006) look for evidence of accrual reversals by examining the behavior of COMPUSTAT ‘special items’ in the years following large positive working capital accruals. They report that special items are unusually large and negative for high accrual firms starting two years after the large positive accruals. Their evidence, however, is subject to several limitations. First, special items include both cash and accrual related charges. Hence, their results cannot be unambiguously attributed to accrual reversals. Second, their paper focuses on working capital accruals, whose reversals are typically not included in special items. For example, SEC rules require that inventory write-downs be included in cost of goods sold[2] and hence they are typically recorded as such by COMPUSTAT.[3] Third, empirical research consistently finds that the biggest earnings and stock price reversals occur in the year immediately following extreme accruals, thus their finding that negative special items do not materialize until two years after the accrual measurement year is inconsistent with the reversal explanation.

A working paper by Zach (2007) examines the role of accrual reversals in explaining the accrual anomaly. Zach argues that accruals tend to be 'sticky', in that firm-years with extreme accruals in one year are more likely to have extreme accruals of the same sign in a subsequent year. He concludes that these reversals are insufficient to explain the accrual anomaly and suggests bankruptcy risk as a competing explanation. In contrast to Zach, we demonstrate that accrual reversals are both economically and statistically significant and that accrual reversals explain both the lower persistence of the accrual component of earnings and the predictable stock returns following extreme accruals.

Our paper is also related to contemporaneous research by Fedyk, Singer and Sougiannis (2010). Using quarterly data, they track extreme abnormal accruals through to their subsequent reversal and show that the accrual anomaly in stock returns is concentrated in the reversal quarters. The key difference between our study and theirs is that we document both the relatively high frequency of extreme reversals and their impact on earnings. Our approach documents the extent to which estimation errors in observed accruals impact the properties of

[2] See EITF 96-9 (1996).

[3] We manually inspected a sample of 19 large inventory write-downs to verify their income statement classification in both the firms' Form 10-Ks and as coded by COMPUSTAT. We found that all 19 of the firms followed EITF 96-9 in classifying their inventory write-downs as part of costs of goods sold on their income statements. However, we found that while COMPUSTAT followed this classification for 12 of the 19 cases, COMPUSTAT removed the write-downs from cost of goods sold and reclassified them as special items for the other 7 cases.

earnings. Our detailed analysis of inventory accruals also enables us to make a direct link between *ex ante* estimation errors in accruals and subsequent predictable accrual reversals.

Finally, our detailed analysis of inventory accruals builds on related research by Thomas and Zhang (2002). Thomas and Zhang show that inventory accruals have a particularly strong negative relation with future stock returns. However, they are unable to distinguish between the several competing explanations for their results. We build on Thomas and Zhang by demonstrating that extreme inventory accruals are particularly prone to estimation errors. We show that inventory accruals exhibit a greater frequency of extreme accrual reversals and this causes the persistence of inventory accruals to be particularly low. We further show that inventory accrual reversals explain the particularly strong negative relation between inventory accruals and future stock returns. Finally, we demonstrate that extreme inventory accrual reversals frequently manifest themselves in the form of inventory write-downs.

2.2 Hypothesis Development

Accruals anticipate probable future economic benefits (e.g., cash inflows) and obligations (e.g., cash outflows). In doing so, they allow the financial effects of current transactions and events to be recognized in the current period rather than when the cash consequences of the transactions and events are realized in the future. As such, most accruals reverse when the cash flows that they anticipate are realized. Thus, the realization of the anticipated cash flows has no direct impact on contemporaneous earnings. But since accruals are estimates of expected future cash flows, the original accrual does not always equal the associated future cash realization. In such cases, the difference between the original accrual and the associated future cash realization must run through earnings. For example, if the subsequent net realizable value of inventory is less than its original cost, inventory and earnings must be reduced accordingly.

We refer to the difference between an original accrual and its associated future cash realization as the *ex post* estimation error in the accrual. Note that *ex post* estimation error may reflect either *ex ante* predictable bias in the original accrual or *ex post* unpredictable error that was not foreseeable at the time the original accrual was made. Our focus is on the extent to which extreme accruals reflect *ex ante* predictable bias of the same sign. Other things equal, a large positive estimation error in an accrual will cause the accrual itself to be large and positive. Thus, extreme accruals are a natural starting point in the search for predictable estimation errors (see Richardson, Sloan, Soliman and Tuna 2005). For example, management may be slow to write down inventory in the face of dwindling demand. This will manifest itself as an initial build up in inventory followed by a subsequent inventory write-down.

The discussion above focuses on specific accrual transactions, while empirical tests using financial statement data must aggregate across a large number of accrual transactions by balance sheet category (e.g., the aggregate inventory accrual over a fiscal year). Since firms are going concerns with persistent earnings and cash flows, we expect their aggregate accruals to persist over time. For example, a firm will typically replace inventory as it is sold, thus replacing a reversing accrual with a new originating accrual. This means that while all specific accrual transactions must reverse, aggregate accruals will only reverse if (i) the firm's underlying business changes; or (ii) the original accrual represents estimation error. Moreover, the reversal of the accrual will only have a direct impact on future earnings in case (ii), where the original accrual represents estimation error. For example, an accrual estimation error of +$1 today will cause earnings to be overstated by $1 today. Upon the discovery of this error in a subsequent period, the accrual will have to be reversed via a corresponding charge of -$1, causing earnings to be understated by $1 in the reversal period.

In summary, accrual estimation errors are associated with both subsequent accrual reversals and subsequent earnings changes. The subsequent reversal is equal in magnitude but opposite in sign to the original error, while the induced change in earnings is twice the magnitude and of the opposite sign to the original error. In this paper, we recognize that accrual estimation errors must reverse and consider the consequences for future accruals, earnings and stock returns.

Our first prediction concerns the high frequency of extreme accrual reversals that will arise if extreme accruals contain a high frequency of predictable estimation errors of the same sign. Since such estimation errors are not expected to be present in the cash component of earnings, we use extreme cash flow reversal rates as a benchmark for evaluating extreme accrual reversal rates.

P1: Relative to extreme cash flows, extreme accruals exhibit a disproportionately high frequency of extreme subsequent reversals.

Our second prediction concerns the contemporaneous association between accrual reversals and earnings changes. Recall that while all accruals must ultimately reverse, these reversals are designed to be offset by anticipated benefits, with no net impact to earnings. This is why accruals are strongly negatively correlated with cash flows (see Dechow, 1994). But to the extent that accruals represent estimation errors, these reversals must run directly through subsequent earnings, thus causing a positive relation between accrual reversals and contemporaneous earnings changes:

P2: Accrual reversals are positively related to contemporaneous earnings changes.

Our third prediction links the reversal of accrual estimation errors to the well-documented lower persistence of the accrual component of earnings. Sloan (1996) first documents the lower persistence of the accrual component of earnings, conjecturing that it arises because the accrual component of earnings is more subjective. Subsequent research has advanced a number of competing explanations for this relation. Following up on Sloan (1996), Richardson et al. (2005) hypothesize that it is attributable to the lower reliability of the accrual component of earnings. In contrast, Fairfield et al. (2003) and Wu et al. (2010) hypothesize that it is attributable to diminishing marginal returns to new investment. We hypothesize that it arises because of the reversal of estimation errors in extreme accruals. While related to the explanations in Sloan (1996) and Richardson et al. (2005), we explicitly identify reversing estimation errors in accruals as the driver of the lower persistence.

P3: Accrual reversals explain the lower persistence of the accrual component of earnings.

Sloan (1996) also shows that accruals are negatively related to future stock returns, attributing this result to investors not fully anticipating the lower persistence of the accrual component of earnings. Since we hypothesize that accrual reversals explain the lower persistence of the accrual component of earnings, we also hypothesize that accrual reversals explain the negative relation between accruals and future stock returns. This generates our fourth prediction:

P4: Accrual reversals explain the negative relation between accruals and future stock returns.

We emphasize that the purpose of *P3* and *P4* is to establish that accrual reversals are the channel through which accrual predict future earnings and stock returns. Accrual reversals themselves are not known until after the fact.

Our next prediction seeks to corroborate the explanation behind our earlier predictions by identifying *ex ante* cross-sectional variation in the likelihood that extreme accruals represent estimation error. Extreme accruals attributable to estimation error should be more likely to reverse and hence they should also have a stronger negative relation with both future earnings changes and future stock returns.

Existing research has modeled the 'normal' component of accruals as an increasing function of contemporaneous sales growth (e.g., Jones, 1991). The intuition motivating this model is that sales growth creates an economic need for additional working capital and hence increased accruals. Thus, accruals that are unrelated to sales growth are considered 'abnormal' and are hypothesized to be more likely to represent measurement error. Consistent with this hypothesis, related research has shown that abnormal accruals are more strongly negatively related to future stock returns (e.g., Xie, 2001). Because abnormal accruals are more likely to represent measurement error, we predict that they are more likely to exhibit extreme reversals.

P5: Extreme accrual reversals are more prevalent for abnormal accruals.

A key contribution of our paper is attributing extreme accrual reversals to the reversal of accrual estimation errors. Accordingly, we would like to rule out other potential explanations for this result. We have inferred that the accrual reversals reflect estimation errors by demonstrating that the reversals cause contemporaneous changes in earnings (see *P2*). But we cannot rule out the possibility that the reversing accruals correctly anticipate their associated benefits and the associated earnings changes are due to other correlated omitted variables.[4] Thus, our sixth prediction involves testing for a direct link between *ex ante* extreme accruals and *ex post* estimation errors in those accruals. We test this prediction using a hand-collected sample of inventory write-downs. Since inventory write-downs represent the reversal of estimation errors

[4] For example, imagine that an existing customer who generally buys one unit each period on credit (paying in the next period) happens to accelerate a purchase such that she is sold two units in the current period and no units in the next period. We would observe an increase in accruals and earnings in the current period, followed by a decrease in accruals and earnings in the next period. Of course, the problem with this story is that we would observe the same behavior in the cash component of earnings if the same facts held, except the customer accelerated a cash purchase. Yet in practice, an increase in the cash component of earnings is not followed by extreme reversals in cash flows and earnings.

in past inventory accruals, we predict that extreme positive inventory accruals will be systematically related to subsequent inventory write-downs:

P6: Extreme positive inventory accruals are associated with an increased frequency and magnitude of subsequent inventory write-downs.

3. Data and Variable Measurement

We use two samples in our analysis. Our main accruals sample is obtained from the COMPUSTAT fundamental annual file. Our second inventory accrual sample uses write-down data that is hand collected from 10-K filings in conjunction with inventory accrual data from the COMPUSTAT fundamental annual file. Stock return data for both samples are obtained from the CRSP monthly returns file. Our first sample spans 1962-2007. We begin our sample in 1962 because COMPUSTAT data prior to 1962 are generally acknowledged to suffer from survivorship bias (Kothari et al. 1995). As in prior research examining accruals, we eliminate all financial services companies (SIC 6000-6999), and limit the sample to domestic firms (popsrc = D and fic = USA) traded on a major US exchange (EXCHD code equal to one, two, or, three). Additionally, we eliminate all firm years that have a change in fiscal year end during the sample period. The size of our second sample is restricted by the cost of hand collecting inventory write-down data and is limited to the calendar years 2001-2004.

The financial variables of interest in this study are accruals (ACC), cash flows (CF), and earnings (INC). The definition of earnings employed in our tests is operating income (COMPUSTAT data item OIADP).[5] We measure accruals (ACC) from the balance sheet as

[5] We use a definition of income that incorporates the origination and reversal of working capital accruals, but avoids other extraneous transitory items. Note that operating income excludes special items, discontinued operations and extraordinary items. Given our focus on working capital accruals, this choice is appropriate (for example, inventory

change in non-cash current assets (COMPUSTAT data item ACT less COMPUSTAT data item CHE) less the change in current operating liabilities (COMPUSTAT data item LCT less COMPUSTAT data item DLC less COMPUSTAT data item TXP). Note that our measure of accruals is restricted to 'current' or 'working capital' accruals and excludes 'non-current' or 'investing' accruals (see Sloan 1996; Richardson, et al. 2005). We make this choice because our focus is on the reversal of accrual estimation errors and because current accruals are typically expected to reverse within the next year. By using current accruals, our empirical analysis can therefore focus on reversals that are likely to occur in the next year, mitigating concerns about loss of power from the omission of longer-term reversals. Cash flows (CF) are measured as the difference between income and accruals. Accrual reversals (ΔACC) are computed as the difference between accruals in the current period and accruals in the previous period. We require the availability of COMPUSTAT data for each of the above variables with the exception of COMPUSTAT data items DLC and TXP (debt in current liabilities and taxes payable), which are set to 0 if missing. We define inventory accruals (INVACC) as the change in inventory (COMPUSTAT data item INVT) and inventory accrual reversals (ΔINVACC) as the change in inventory accruals. Our large sample consists of 151,157 firm-year observations from 1962-2007 with accruals, cash flows and income data available in both periods t and t+1 and stock return data in period t+1.

We hand collect inventory write-down amounts from firms' 10-K filings. We searched all 10-K filings on the DirectEdgar database covering calendar years ending in 2001-2004. We began by conducting a keyword search for any occurrence of the word 'write' within ten words of the word 'inventory.' We then filtered these results using the CIK numbers of all firms that

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accrual originations and reversals are reflected in cost of goods sold, while receivable accrual originations are reflected in revenues or SG&A expense (bad debt expense).

appeared in both the CRSP and COMPUSTAT databases for the years 2001-2004 and were traded on a major US exchange (EXCHD code equal to one, two, or, three). After filtering we were left with 5,638 filings. We then searched and read through each 10-K for discussion or documentation of an inventory write-down during the fiscal year. Upon finding evidence of an inventory write-down, we collected the amount of the inventory write-down from the Form 10-K[6]. Our search yielded 1,869 firm-year observations reporting inventory write-down amounts and having the necessary data for inclusion in our sample. Our write-down sample includes all firm-year observations from the larger 1962-2007 sample with calendar years ending in 2001-2004. Inventory write-down (WD) is set equal to the hand collected inventory write-down amount for the 1,869 firm-year observations described above and zero otherwise. There are 15,342 total firm-year observations in our write-down sample, and so we have non-zero write-down amounts for just over 10% of the observations.

We scale all financial variables in our sample by average total assets (COMPUSTAT data item AT). As in previous research, we find that the distributions of our scaled financial variables are characterized by a small number of extreme outliers. We therefore follow the standard procedure of winsorizing observations with an absolute value greater than 1. These winsorization procedures makes sense on *a prior* grounds, because situations where individual financial variables exceed more than 100 percent of average total assets are unusual and we do not want to give these observations excessive weight in our analysis. [7]

[6] Approximately 10 percent of firms acknowledge an inventory write-down in the 10-K, but fail to separately report the inventory write-down amount. We eliminate these firms from our write-down sample.
[7] We replicated our empirical tests on a variety of samples to evaluate the robustness of our results. This included (i) trimming rather than winsorizing accounting variables with an absolute value greater than 100% of total assets; (ii) eliminating observations with stock prices less than $5; (iii) eliminating observations in the bottom decile of market capitalization and (iv) eliminating observations where goodwill changed by more than 5% of beginning of period total assets (to control for unusual M&A activity). The results are qualitatively similar to those reported in the paper.

Our final prediction, *P6*, requires a measure of 'abnormal' accruals. Previous research has estimated abnormal accruals as the residuals from regressions of accruals on the change in sales (see Jones, 1991). A shortcoming of this approach is that the estimated parameters are subject to error, resulting in noisy estimates of abnormal accruals. We therefore adopt a more parsimonious approach that employs sensible economic priors regarding the relation between normal accruals and sales growth. Specifically, we assume that the normal growth rate in working capital should be equal to the growth rate in sales, thus attributing any remaining growth in working capital to abnormal accruals.[8] This results in the following measures of normal accruals (NORMACC) and abnormal accruals.

$$NORMACC_t = WC_{t-1}*(Sales_t/Sales_{t-1})$$

$$ABACC_t = ACC_t - NORMACC_t$$

The above measurements are made before deflating WC and ACC by average total assets, and both NORMACC and ABACC are subsequently deflated by average total assets.

Our returns tests employ twelve-month buy-and-hold stock returns (RET) inclusive of distributions and adjusted for delistings. The returns are computed from the CRSP monthly file. Our annual return measurement interval begins in the fourth month after the previous fiscal year end to allow time for the annual financial information to be made publicly available.

4. Large Sample Results

4.1 Descriptive Statistics

Table 1 presents descriptive statistics for our main variables of interest: accruals (ACC), accrual reversals (ΔACC), cash flows (CF), cash flow reversals (ΔCF), inventory accruals

[8] Recall that non-cash working capital is dominated by accounts receivable, inventory and accounts payable. Other things equal, these accounts should grow in proportion to the number of units produced or sold. Thus, the assumption of a one-to-one correspondence between sales growth and working capital growth is justified *a priori*.

(INVACC), inventory accrual reversals (ΔINVACC), change in income (ΔINC), and stock return (RET). Panel B presents both Pearson and Spearman pair-wise correlations between these variables. Consistent with the results documented in Sloan (1996), accruals are negatively correlated with both next period's change in income and next period's stock return. Consistent with Thomas and Zhang (2002), we also document strong negative correlations between inventory accruals and both the change in future income and the future stock return.

Consistent with Dechow (1994), there is a strong negative relation between accruals and cash flows. Note that the correlation is even more negative between accrual reversals and cash flow reversals, illustrating the primary role of accruals in eliminating timing and matching problems in cash flows. However, consistent with our prediction *P2*, there is strong positive correlation between accrual reversals and change in income. The Pearson correlation between ΔACC_{t+1} and ΔINC_{t+1} is 0.254, while the Pearson correlation between ΔINV_{t+1} and ΔINC_{t+1} is 0.144. These positive correlations are consistent with the existence of significant reversing estimation error in accruals. We emphasize that while accruals are a component of earnings, the positive relation between accrual reversals and earnings changes is not purely mechanical. If accruals' only impact was to eliminate temporary timing and matching problems with cash flows, then there would not be a elation between accruals reversals and earnings changes.

Table 2 provides preliminary descriptive evidence on accrual reversals using quintile portfolio transition matrices based on earnings components in the current year (t) and the subsequent year (t+1). The matrices show the relative frequencies with which firms transition between extreme quintiles. We express these frequencies as a percentage of the total sample size, such that they sum to 100 percent across all 25 cells in each transition matrix. In the absence of serial correlation, we expect 4 percent of the observations to fall within each cell (i.e., 100% / 25 cells = 4% / cell). Positive serial correlation will cause a greater proportion of observations to fall in and around the main diagonal cells (top left through bottom right) and a lesser proportion of the observations to fall in the extreme minor diagonal cells (bottom left and top right). Negative serial correlation (i.e., reversals) will cause a greater proportion of the observations to fall in and around the extreme minor diagonal cells.

We begin by reporting the transition matrix for earnings (INC) in panel A of table 2. Each cell reports the percentage of the total sample falling into that cell. For example, 14.28 percent of the observations fall in the top left (t=Bottom, t+1=Bottom) cell. To facilitate the identification of cells with high percentages, we shade all cells with greater than 4 percent of the observations. For earnings, we see clear evidence of a concentration of observations down the main diagonal and an absence of observations in the extreme minor diagonal cells. For example, 28.76 percent of the observations fall in the two extreme main diagonal cells, while only 0.88 percent of the observations fall in the two extreme minor diagonal cells. There is strong evidence of positive serial correlation and little evidence of extreme reversals. Panel B of table 2 reports the transition matrix for cash flows (CF). This transition matrix closely mirrors the pattern for earnings in panel A, though the concentration down the main diagonal is somewhat weaker. 21.74 percent of the observations fall in the two extreme main diagonal cells, while only 3.06 percent of the observations fall in the two extreme minor diagonal cells. The somewhat weaker positive serial correlation for cash flows likely reflects the mismatching of the cash consequences of transactions (Dechow 1994).

Panel C of table 2 reports the transition matrix for accruals (ACC). This matrix is strikingly different from those in the previous two panels. While there is still evidence of a concentration of observations down the main diagonal, it is much weaker than in the first two panels. More importantly, we now see an additional concentration of observations in the extreme minor diagonal cells. For example, 12.01 percent of the observations fall in the two extreme main diagonal cells, while 9.72 percent of the observations fall in the two extreme minor diagonal cells. Meanwhile, the cells in the off-diagonals contain the lowest proportion of the observations. For example, the transition from the 'Top' accrual quintile in period t to the '3' accrual quintile in period t+1 contains only 2.26 percent of the observations. This evidence suggests that accruals most frequently fall into one of two categories. They either exhibit strong positive serial correlation, as we saw for earnings and cash flows, or they exhibit extreme negative serial correlation, as predicted by *P1*.

Panel D of table 2 reports the transition matrix for inventory accruals (ΔINV). It displays a similar pattern to the previous panel, confirming that inventory accruals are a major contributor to extreme accrual reversals. One distinguishing feature of inventory accruals is the relatively high frequency of observations in the bottom left cell (t=Top, t+1=Bottom). This cell has 5.69% percent of the observations for inventory accruals versus 5.10% percent for all accruals, suggesting that extremely positive inventory accruals are particularly prone to extreme reversals. This evidence is consistent with our *P5*, whereby extremely positive inventory accruals are more susceptible to subsequent write-downs.[9]

Table 2 provides clear evidence of extreme accrual reversals. *P2* predicts that if these extreme accrual reversals result from the reversal of estimation error in accruals, they should cause a corresponding change in contemporaneous earnings. Table 3 provides descriptive evidence that this is the case. Panels A and B of table 3 first report the magnitude of the mean

[9] Note that there is also weaker evidence of extreme reversals from low inventory accruals to high inventory accruals. Since inventory write-ups are not permitted, these reversals must have a different source. One possibility is that write-down firms take excessive write-downs, causing inventory to subsequently increase when it is replenished at replacement cost. This would be consistent with Moehrle's (2002) evidence that firms systematically overstate and subsequently reverse restructuring liabilities.

accrual reversals in each cell of the transition matrices for aggregate accruals and inventory accrual respectively. As expected, we see the biggest positive reversals in the 'Bottom' to 'Top' cell (0.302) and the biggest negative reversals in the 'Top' to 'Bottom' cell ((-0.336).

Panel C of table 3 reports the mean change in income (deflated by total assets) for each cell, with the final column reporting the overall row means. Consistent with Sloan (1996), there is a negative relation between accruals in period t and the change in income between period t and period t+1, as the change in income is monotonically decreasing as we move down the final column. Inspection of the other columns sheds light on the extent to which the pattern in the final column is attributable to extreme accrual reversals. Consistent with *P2*, the biggest increase in income is observed in the top right cell (0.056), while the biggest decrease in income is observed in the bottom left cell (-0.082). In other words, the negative relation between accruals and changes in future earnings is attributable to the higher frequency of extreme accrual reversals combined with their associated impact on future earnings. Panel D of table 3 reports similar results for inventory accruals. Note in particular that the largest reduction in income is found in the 'Top' to 'Bottom' cell (-0.052). Recall that this is also the cell where we saw a particularly high frequency of observations in panel D of table 2 and so this is the main contributor to the negative row mean of -0.027 for the 'Top' quintile of period t inventory accruals.

Panel E of table 3 reports the mean stock returns for cells in the accrual transition matrices. The pattern for returns generally corresponds to the pattern for earnings changes. The top right (bottom left) cells have relatively high (low) mean returns. Again, we see that the row means in the final column are monotonically decreasing and we can attribute this pattern to the combination of high frequencies of observations along the minor diagonal cells combined with the decreasing pattern in returns as we move from right to left down the minor diagonal. This panel suggests that the predictable negative relation between period t accruals and period t+1 returns arises because investors do not anticipate the predictable earnings changes that are caused by extreme accrual reversals. Panel F of table 3 provides similar evidence for inventory accruals. Of particular note is the extremely low mean return in the bottom left cell (-0.007), which is the same cell where we observe a particularly large reduction in earnings in panel D of table 3 and a particularly high frequency of accrual reversals in panel D of table 2. These results indicate that the particularly strong negative relation between inventory accruals and future returns (Thomas and Zhang, 2002) is consistent with investors not anticipating the relatively high frequency of extreme reversals for positive inventory accruals and their associated impact on contemporaneous earnings. In the next section, we will show that these reversals frequently take the form of inventory write-downs.

To summarize, tables 1, 2 and 3 provide preliminary descriptive evidence consistent with predictions *P1*, *P2*, *P3* and *P4*. Extreme accruals exhibit a relatively high proportion of subsequent reversals, and these reversals are associated with contemporaneous earnings changes and stock returns. We next turn to formal statistical tests of our predictions.

4.2 Tests of Large Sample Predictions

Table 4 reports formal statistical tests of prediction *P1*, that extreme accruals exhibit a disproportionately high frequency of extreme subsequent reversals. To conduct these tests, we construct a series of dummy variables that take the value of one for observations belonging to the extreme quintile of the distribution of each variable and zero otherwise. We examine four variables (INC, CF, ACC and INVACC) and distinguish between the highest quintile (H) and lowest quintile (L), thus constructing a total of eight dummy variables (HINC, LINC, HCF, LCF, HACC, LACC, HINVACC, LINVACC). For each variable, we then regress each extreme quintile dummy variable for period t+1 on the corresponding two extreme dummy variables for period t. For an uncorrelated series, we expect no relation between extreme quintile membership in period t and extreme quintile membership in period t+1. For a positively serially correlated series, we expect a positive relation between memberships in corresponding extreme quintiles in adjacent periods. Finally, for a negatively serially correlated series (i.e., one exhibiting extreme reversals), we expect a positive relation between memberships in opposite quintiles in adjacent periods. Thus, *P1* predicts that there will be positive relations between $LACC_{t+1}$ and $HACC_t$ and between $HACC_{t+1}$ and $LACC_t$.

We begin by reporting the extreme quintile regression results for earnings (INC) in panel A of table 4. Here we see strong evidence of a positive relation between the same extreme quintiles in adjacent periods. The t-statistic on the relation between $HINC_{t+1}$ and $HINC_t$ is 85.70 while the t-statistic on the relation between $LINC_{t+1}$ and $LINC_t$ is 48.06. There is also evidence of a significant negative relation between the opposite extreme quintiles in adjacent periods. Thus, consistent with the evidence in panel A of table 2, there is strong evidence of positive serial correlation in earnings. The results for cash flows (CF) are qualitatively similar to those for earnings, though they are weaker in economic magnitude and statistical significance. This most likely reflects the fact cash flows do not always reflect the financial consequences of transactions and events in the period that the transactions and events occur, and thus provide a more noisy measure of financial performance (Dechow, 1994).

The results for accruals (ACC) are strikingly different from those for earnings and cash flows. In particular, while they exhibit a strong positive serial correlation between the same extreme quintiles in adjacent periods, they also exhibit a strong positive correlation between the opposite extreme quintiles in adjacent periods. Specifically, the t-statistic on the relation between $HACC_{t+1}$ and $LACC_t$ is 14.07 while the t-statistic on the relation between $LACC_{t+1}$ and $HACC_t$ is 13.70. These results confirm our prediction of a disproportionately high frequency of extreme reversals for accruals. Unlike earnings and cash flows, accruals do not display simple positive serial correlation. Instead, accruals contain a mix of both extreme positively serial correlated observations and extreme negatively serially correlated observations.

The final set of results in table 4 is for inventory accruals (ΔINV). These results closely mirror those for accruals, with one notable difference. For inventory accruals, reversals from $HINVACC_t$ to $LINVACC_{t+1}$ are somewhat stronger than reversals from $LINVACC_t$ to $HINVACC_{t+1}$. These differences have a straightforward interpretation. Inventory accruals are asset accruals, and so they are positive when they originate and negative when they reverse, leading to a higher frequency of high to low reversals. Our aggregate accrual measure, on the other hand, contains a mix of asset and liability accruals, and liability accruals are negative when they originate and positive when they reverse (e.g., Moehrle, 2002).

Table 5 illustrates the impact of extreme accrual reversals on the time-series properties of earnings. Previous research has shown that earnings and cash flows are strongly positively serially correlated (i.e., slowly mean reverting), while accruals are weakly positively serially correlated, (i.e., rapidly mean reverting). Table 5 reports autoregressions for INC, CF, ACC and INVACC. Consistent with previous research, we see large positive coefficients on INC (0.841) and CF (0.679) and much smaller positive coefficients on ACC (0.025) and INVACC (0.120).

We next repeat the autoregressions after including interactive dummy variables to control for extreme reversals. This is accomplished by creating new indicator variable that equal one for observations with extreme quintile reversals between periods t and t+1 and zero otherwise. To facilitate interpretation, we create separate dummy variables for low to high reversals ('LH' prefix') and high to low reversals ('HL' prefix). We expect the interactions to load with negative coefficients in all autoregressions, because the interactions pick out the extreme reversals. More importantly, we expect that the interactions will load with greater statistical significance, add more explanatory power and lead to greater increases in the main autoregressive coefficients for ACC than for INC and CF. This is because of the greater frequency of extreme reversals for ACC.

The results are consistent with our expectations. First, the coefficients on the interactions are all significantly negative. Second, the t-statistics on these coefficients are greater for ACC than for INC and CF. Third, the increases in explanatory power are much greater for ACC and INVACC. For example, the adjusted R^2 increases from 0.470 to 0.585 in the CF autoregression, while it increases from 0.001 to 0.274 in the ACC autoregression. Fourth, the autoregressive coefficients increase in all regressions, but the increases are much greater for ACC and INVACC. For example, the autoregressive coefficient on CF increases from 0.679 to 0.761, while the corresponding coefficient on ACC increases from 0.025 to 0.397. The key take-away from this table is that the apparently weaker serial correlation in accruals relative to cash flows and earnings is in large part attributable to the greater frequency of extreme accrual reversals.

These results highlight an important feature of the time series behavior of accruals. Previous research has modeled accruals as a simple autoregressive process, resulting in the conclusion that accruals are rapidly mean reverting. Our results show that this simple characterization of accruals is misleading, because accruals consist of two distinct underlying processes. The first consists of 'good' accruals that follow a similar process to cash flows, displaying strong positive serial correlation. The second consists of estimation errors that display strong negative serial correlation. It is only by mixing these two distinct processes that one reaches the mistaken inference that accruals are rapidly mean reverting.

We next conduct tests of prediction *P2*, that accrual reversals are contemporaneously related to innovations in earnings. Recall from the discussion in section 2 that accrual reversals are supposed to be offset by anticipated benefits, such that their reversals have no net impact on earnings. But to the extent that some accruals represent estimation errors, their reversals must run directly through earnings, causing a positive relation between accrual reversals and contemporaneous earnings. We test this prediction by regressing the change in earnings for period t+1 (ΔINC_{t+1}) on accrual reversals for period t+1 (ΔACC). If accrual reversals are completely offset by their anticipated benefits, we expect a coefficient of zero on ΔACC_{t+1}. On the other hand, if accruals consist entirely of estimation error, then we expect a coefficient of one on ΔACC_{t+1}. Pooled cross-sectional regressions are reported in table 6. The coefficient on ΔACC_{t+1} in the second regression is 0.286 and highly statistically significant (t=20.09). The magnitude of the coefficient indicates that an average of 28.6 percent of accrual reversals have a direct impact on future earnings and are thus consistent with the reversal of estimation error. The remaining 71.4 percent of accrual reversals have no contemporaneous earnings impact, confirming that the first order effect of accruals is to perform their intended role of mitigating timing mismatches in cash flows (Dechow, 1994). Nevertheless, our results are consistent with the existence of estimation errors in accruals that have an economically and statistically significant impact on earnings.

The results in table 6 also test *P3*, that after controlling for accrual reversals, the accrual component of earnings is no longer less persistent than the cash flow component of earnings. The first row of table 6 reports the basic persistence regression. Consistent with Sloan (1996), the coefficient on CF_t (-0.135) is larger than the coefficient on ACC_t (-0.246), confirming that the accrual component of earnings is less persistent than the cash flow component of earnings.[10] The second regression of Table 6 adds ΔACC_{t+1} to the persistence regression. Consistent with *P3*, the negative coefficient on ACC_t disappears. This result clearly demonstrates that it is only in cases where accruals subsequently reverse that we observe low earnings persistence. Another way of thinking about this result is that high accrual firms have lower future earnings because of lower future accruals and not because of lower future cash flows. The final row of Table 6 replaces ΔACC_{t+1} with ΔCF_{t+1}. The key takeaway from this regression is that after controlling for cash flow reversals, the negative coefficient on ACC gets even more negative (-0.568). The regression coefficient tells us that 56.8% of all accruals that don't anticipate a change in future cash flows in the next period end up reversing in the next period. Recall that the role of accruals is to anticipate future cash flows, so by controlling for future cash flows, we have isolated the *ex post* errors in accruals.

Table 7 reports tests of *P4* that accrual reversals explain the negative relation between accruals and future stock returns. This table basically replicates the regressions in table 6 using RET_{t+1} in place of INC_{t+1} as the dependent variable. We also control for other well-documented return predictors including book-to-market ratio (BM), market capitalization (SIZE), momentum (MOM6) and long-term reversal (MOM36). The first row confirms the widely documented negative relation between accruals and subsequent stock returns. Note also that the statistical significance of the accruals and the other return predictors is lower than in past research. This is because we estimate standard errors clustering by firm and year (see Gow, Ormazabal and Taylor, 2010). The second regression in table 7 demonstrates that the predictable negative

[10] Note that Sloan (1996) uses INC_{t+1} as the dependant variable, while we use ΔINC_{t+1} as the dependent variable. The two specifications are equivalent, except that our specification involves subtracting INC_t from both sides, hence reducing the estimated coefficients on both CF_t and ACC_t by one (i.e., INC-ACC-CF=0).

relation between accruals and future stock returns arises because investors do not anticipate the implications of the lower persistence of accruals for future earnings changes. This regression includes ΔINC_{t+1}, which loads with a significant positive coefficient. Note that the significance of ΔINC_{t+1} is not surprising, because this variable is measured *ex post* with RET_{t+1}. The important takeaway is that the negative coefficient on ACC_t disappears in this regression. This result corroborates Sloan's (1996) conclusion that accruals predict future stock returns <u>because</u> of their ability to predict future earnings changes.[11] *P4* provides further insight onto this result by further tracing the predictable stock returns back to the extreme accrual reversals that underlie the predictable earnings changes. The third regression in table 6 directly tests *P4* by replacing ΔINC_{t+1} with ΔACC_{t+1}. Consistent with *P4*, these results show that upon controlling for accrual reversals, the negative relation between accruals and subsequent stock returns disappears. The fourth regression in table 4 replaces ΔINC_{t+1} with ΔCF_{t+1}. The negative coefficient on accruals is even stronger in these regressions, confirming that the negative relation between accruals and future stock returns arises from its ability to forecast future earnings changes driven by accrual reversals rather than cash flow reversals. Intuitively, controlling for *ex post* cash flow changes isolates accruals that do not map into future cash flows and are therefore more likely to represent estimation error.

Our next prediction, *P5*, is that extreme accruals that are driven by abnormal accruals (ABACC) are more likely to reverse than extreme accruals that are driven by normal accruals (NORMACC). Recall that NORMACC captures accruals that correspond to contemporaneous sales growth, while ABACC captures accruals that do not correspond to contemporaneous sales growth. Panel A of table 8 reports accrual transition matrices for NORMACC and ABACC.

[11] Sloan (1996) demonstrates this result using the Mishkin (1983) testing framework, though our approach of directly incorporating the change in income in the stock return regression is econometrically equivalent.

These transition matrices correspond to the one in Panel C of table 2, except that the period t ranking is based on NORMACC in the first matrix and ABACC in the second matrix. Thus, *P5* predicts more extreme reversals in the second matrix. The results are consistent with this prediction. There is no evidence of an unusually high frequency of extreme reversals in the first matrix, while there is strong evidence of extreme reversals in the second matrix. In particular, over 12% of the total observations fall in the two extreme reversal cells. Panel B of table 8 tests for the statistical significance of the extreme reversals along the same lines as the regressions in panel C of table 4. The only difference is that we include separate extreme dummy variables for extreme quintiles of NORMACC and ABACC as explanatory variables. Recall from panel C of table 4 that both extreme persistence and extreme reversals were statistically significant for accruals. The results in panel C of table 8 illustrate that extreme reversals are no longer significant for NORMACC, while they are even more highly significant for ABACC. Thus, while we use an admittedly crude method to parse accruals into normal and abnormal components, we have clearly isolated accruals that are more likely to reverse in the abnormal component.

Panels C and D of table 8 investigate whether the greater frequency of reversals in ABACC can be used to enhance the prediction of future earnings changes and stock returns. To conduct these tests, we first create three new indicator variables. The first variable equals HACC-LACC. Recall that HACC takes the value of 1 when ACC is in the highest quintile, while LACC takes the value of 1 when ACC is in the lowest quintile. Thus, the new indicator variable takes the value of 1 when ACC is extremely high and -1 when ACC is extremely low. The presence of extreme accrual reversals in extreme ACC quintiles should lead HACC-LACC to have a negative relation with future earnings changes and stock returns. We also compute corresponding indicator variables for ABACC and NORMACC. Because extreme accrual reversals are more likely for ABACC than NORMACC, we predict that HABACC-LABACC will have the stronger negative relation with the future earnings changes and stock returns. The first regression in panel C of table 8 first confirms that HACC-LACC has the predicted negative relation with future earnings changes (t=-17.14). The next regression shows that this negative relation is stronger for HABACC-LABACC (t=-20.07) than for HNORMACC-LNORMACC (t=13.17).[12] The first regression in panel D of table 8 confirms that HACC-LACC has the predicted negative relation with future stock returns (t=-3.19). It is noteworthy that the statistical significance of HACC-LACC exceeds that of ACC in the first row of table 7. Focusing on extreme accruals reveals a stronger negative relation. The next regression shows that this negative relation is even stronger for HABACC-LABACC (t=-6.07) than for HNORMACC-LNORMACC (t=-0.46). In summary, we show that a relatively crude *ex ante* technique for isolating accrual estimation errors enhances our ability to predict extreme accrual reversals, future earnings changes and future stock returns. These results suggest that the use of more sophisticated techniques to identify accrual estimation errors should result in even greater predictive power.

5. Inventory Write-down Sample Results

In this section, we conduct a detailed analysis of inventory write-downs. This analysis corroborates our large sample analysis by directly linking *ex ante* extreme accruals to the *ex post* reversal of estimation errors. Our large sample analysis is consistent with this link, in that we find evidence of extreme accrual reversals impacting contemporaneous earnings. By analyzing a

[12] The estimated parameters are not directly comparable as the natural ranges of the explanatory variables have been standardized.

sample of inventory write-downs, we can directly test for a relation between past extreme accruals and the reversal of estimation errors. Recall that our analysis of inventory write-downs is based on a comprehensive sample of hand-collected inventory write-downs during 2001-2004. We first provide descriptive statistics for our inventory write-down sample and we then test *P6*, predicting that extreme positive inventory accruals are more likely to lead to subsequent inventory write-downs.

Our sample of write-downs consists of 1,869 firm-year observations spanning a number of industries, with a concentration in industries where inventory obsolescence is more common (equipment, computers and retail). The write-downs are evenly distributed across the 4 years in our sample, with no single year comprising more than 30% of the sample. Table 9 presents descriptive statistics for the write-down sample. Panel A provides descriptive statistics for average total assets, income divided by average total assets (INC), inventory accruals (INVACC), inventory accrual reversals (ΔINVACC), inventory write-downs and inventory write-downs divided by average total assets (WD). Note that inventory write-downs are recorded as negative amounts, consistent with their impact on earnings. Write-down observations are characterized by negative earnings, negative inventory accruals and negative inventory accrual reversals. WD is left skewed with a mean of -2.5 percent and a median of -1.0 percent.

Panel B presents Pearson and Spearman pair-wise correlations between inventory write-down, past and current inventory accruals, inventory accrual reversals and changes in past and current income. Write-downs are, not surprisingly, positively associated with contemporaneous inventory accruals, as the write-downs directly cause a reduction in inventory. Similarly, write-downs are positively correlated with contemporaneous inventory accrual reversals. More interestingly, we see that write-downs are negatively correlated with last period's inventory accruals. This is consistent with *P6*, whereby write-downs are related to the reversal of large positive inventory accrual estimation errors made in the prior period. Inventory write-downs are also positively correlated with contemporaneous changes in income. This result is consistent with *P2*, whereby reversing accrual estimation errors cause corresponding reductions in contemporaneous earnings.

Table 10 provides additional descriptive evidence on the relation between inventory write-downs and inventory accruals. It reports a transition matrix for all available COMPUSTAT firm-years during 2001-2004 based on quintile ranks of inventory accruals in years t and t+1 respectively. The first row in each cell lists the percentage of all observations falling into that cell, essentially replicating the analysis in panel D of table 2 for the write-down sample period. Consistent with the evidence in panel D of table 2, we see a relatively high frequency of extreme inventory accrual reversals. For example, 6.77 percent of the observations switch from the top inventory accrual quintile in period t to the bottom inventory accrual quintile in period t+1.

The second row in each cell reports the percentage of total period t+1 inventory write-down firm-years that fall into each cell. If inventory write-downs are unrelated to current and prior inventory accruals, we would expect 1% of the write-downs to fall into each of these cells. But we clearly expect a negative relation between period t+1 inventory write-downs and period t+1 inventory accruals, because inventory write-downs manifest themselves as negative inventory accruals. This should translate to a greater percentage of write-downs in the first column of table 10. More importantly, *P6* predicts that there will also be a positive relation between extreme positive inventory accruals in period t and write-downs in period t+1. This is exactly what we see, with 16.16 percent of the write-downs concentrated in the bottom left cell (top quintile in period t to the bottom quintile in period t+1).

The third row in each cell reports the magnitude of the average period t write-down as a percentage of total assets. Here we see that the largest write-downs occur in the bottom left cell (-4.8 percent of total assets), confirming our prediction that the largest write-downs are primarily driven by the reversal of estimation errors in extreme positive inventory accruals from period t. The results in Table 10 demonstrate the role of accrual estimation errors in driving extreme accrual reversals. In particular, we see that the frequency and magnitude of inventory write-downs are particularly high following periods of extreme positive inventory accruals.

In order to formally test *P6*, we estimate pooled cross-sectional regressions of inventory write-downs (WD_{t+1}) on prior period inventory accruals ($INVACC_t$). *P6* predicts a negative relation between extreme positive prior inventory accruals and inventory write-downs. We therefore employ a dummy variable that takes the value of one for firms in the top quintile of prior period inventory accruals and zero otherwise (HINVACC). HINVACC is interacted with INVACC, with *P6* predicting a negative coefficient on the interaction. Moreover, the magnitude of this coefficient is an estimate of the proportion of extreme positive inventory accruals that are subsequently written down.[13] Note that all of our tests to this point assume that accrual estimation errors reverse within one year. Given our focus on working capital accruals, this assumption seems reasonable. It is, however, possible that some accrual estimation errors may take more than one year to reverse.[14] We allow for this possibility by including both period t and period t-1 INVACC as explanatory variables. We also include the level of inventory at the

[13] Note that WD_t is censored above at 0, raising the issue of whether estimation of a tobit model is appropriate. It is not because the tobit model is only applicable in those cases where the latent variable can take the unobserved values (Maddala 1988). As a practical matter, we get qualitatively similar results using tobit estimation.
[14] For example, management could cover up the reversal of prior period accrual estimation errors by originating new accrual estimation errors. This is what happened in the infamous case of Crazy Eddie, in which management falsified inventory count sheets for 3 years in a row (http://www.sec.gov/litigation/litreleases/lr15251.txt).

beginning of the period, since this represents the cumulative impact of all previous period inventory accruals. Finally, we include period t non-inventory accruals (ACC-INVACC) and cash flows (CF) in the regressions as controls.

The regression results are presented in table 11. The first row shows the results from a regression of WD_{t+1} on inventory accruals from period t. Consistent with *P6*, the coefficient on $INVACC_{t-1}$*HINVACC is negative and statistically significant (-0.073, t=-5.15). The magnitude of this coefficient indicates that over 7% of extreme positive inventory accruals are subsequently written down. The coefficient on $INVACC_{t-1}$ is positive and significant. This result highlights our earlier finding that after controlling for extreme accrual reversals, remaining accruals tend to persist. The coefficients on non-inventory accruals and cash flows are both positive, suggesting that firms with better underlying earnings performance (exclusive of inventory accruals) are less likely to report write-downs. Finally, the coefficient on INV_{t-1} is significantly negative, indicating that inventory accruals that are more than one year old also help to predict inventory write-downs. The second row of table 10 includes $INVACC_{t-1}$ and its corresponding interaction. These results confirm that extreme positive accrual estimation errors can take up to two years to reverse. The coefficient on $INVACC_{t-1}$*$HINVACC_{t-1}$ is -0.028 (t=-2.74) indicating that a further 3% of extreme positive inventory accruals are written down after 2 years.

In summary, our detailed analysis of inventory write-downs corroborates the interpretation of our large sample results. Extreme positive inventory accruals lead to a disproportionately high frequency of future inventory write-downs, with around 10% of all extreme positive inventory accruals being subsequently reversed through a write-down. These results confirm our hypothesis that extreme positive inventory accruals contain a disproportionately high concentration of positive accrual estimation errors.

6. Conclusions

We provide evidence that extreme accruals contain a disproportionately high frequency of accrual estimation errors of the same sign. We also show that the reversal of these accrual estimation errors explains both the lower persistence of the accrual component of earnings and the predictable stock returns following extreme accruals. Our evidence indicates that extreme accruals belong to two distinct categories. The first consists of estimation errors that subsequently reverse and impact net income. The second consists of 'good' accruals that are persistent and have no direct impact on subsequent earnings. Our evidence corroborates and refines Sloan's (1996) original explanation for the accrual anomaly. In particular, it suggests that the predictable earnings changes and stock returns following extreme accruals result from the predictable reversal of estimation errors in extreme accruals.

Our research highlights a number of avenues for further research. One avenue is to establish the relative importance of competing explanations for the estimation errors in extreme accruals. There are at least four non-mutually exclusive alternatives. The first is deliberate and proactive management/manipulation of earnings (e.g., Xie, 2001). For example, there are numerous well-documented cases in which managers have booked fictitious inventory to temporarily inflate earnings. Second, managers may be slow to adjust their accrual estimates in response to changing economic conditions (e.g., Thomas and Zhang 2002). For example, management may be reluctant to write down inventory in the face of slowing demand in the hope that demand may recover. Third, biased measurement rules mandated by GAAP (e.g., Penman and Zhang 2002). For example, requirements that firms defer recognition of revenue even when most of the service has been provided will cause negative accrual estimation errors in times of growth that will reverse as growth slows. Fourth, managerial hubris may lead to systematic overinvestment, resulting in positive accrual estimation errors at the time these investments are capitalized (e.g., Titman, Wei and Xie 2004).

A second and related opportunity for further research is to more completely document the mechanisms through which estimation errors in extreme accruals originate and reverse. Our analysis of inventory accruals directly ties extreme positive inventory accruals to subsequent inventory write-downs. Future research can study other categories of accruals and document the nature and extent of their subsequent reversals. For example, extreme PP&E accruals are likely to reverse through PP&E write-downs. Future research can also attempt to refine models of normal and abnormal accruals to improve *ex ante* identification of accrual estimation errors.[15]

A third opportunity for further research is to use information in accrual reversals to identify accrual estimation errors and earnings management in *ex post* analyses. For example, academic tests for earnings management typically focus on the magnitude of accruals in the hypothesized earnings management year. The power and specification of these tests could be improved by incorporating related accrual reversals. A recent working paper by Dechow, Hutton, Kim and Sloan (2011) pursues this opportunity.

Our findings also have implications for practitioners, including accountants, auditors, managers, investors and regulators. We show that accruals are systematically biased in that extreme positive (negative) accruals contain systematic positive (negative) estimation error. For accountants, auditors and managers, this highlights an opportunity to improve earnings quality by scrutinizing and adjusting extreme accruals. For investors, this highlights the importance of distinguishing between the cash and accrual components of earnings and analyzing extreme accruals to identify potential distortions in earnings. Moreover, extreme accruals are a crude

[15] Ohlson (2010) provides a framework for modeling abnormal accruals.

indicator of estimation error and more detailed fundamental analysis should produce more refined estimates of accrual estimation error. For regulators, our findings highlight a limitation of allowing managerial discretion in the timing of accrual reversals. For example, our evidence indicates that managers fail to take timely inventory write-downs. This evidence further supports the contention in Ramanna and Watts (2010) that accounting standards allowing greater managerial discretion promote managerial opportunism rather than timely information revelation.

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Table 1
Sample descriptive statistics and pair-wise correlations
(151,157 firm-years from 1962-2007)

Panel A: Univariate statistics

	Mean	Std. Dev	25%	Median	75%
ACC_t	0.021	0.114	-0.021	0.013	0.061
ΔACC_{t+1}	-0.009	0.161	-0.059	-0.002	0.049
CF_t	0.025	0.212	-0.020	0.066	0.130
ΔCF_{t+1}	0.001	0.168	-0.062	-0.001	0.060
$INVACC_t$	0.018	0.075	-0.002	0.004	0.035
$\Delta INVACC_{t+1}$	-0.006	0.100	-0.025	0.000	0.021
ΔINC_{t+1}	-0.008	0.134	-0.040	-0.002	0.027
RET_{t+1}	0.146	0.850	-0.255	0.032	0.352

Panel B: Pair-wise correlations - Pearson (above) and Spearman (below) diagonal

	ACC_t	ΔACC_{t+1}	CF_t	ΔCF_{t+1}	$INVACC_t$	$\Delta INVACC_{t+1}$	ΔINC_{t+1}	RET_{t+1}
ACC_t	-	-0.691	-0.298	-0.298	0.621	-0.362	-0.146	-0.027
ΔACC_{t+1}	-0.619	-	0.311	-0.699	-0.347	0.520	0.254	0.066
CF_t	-0.315	0.355	-	-0.408	-0.175	0.184	-0.152	0.041
ΔCF_{t+1}	0.436	-0.693	-0416	-	0.242	-0.375	0.441	0.078
$INVACC_t$	0.581	-0.289	-0.121	0.182	-	-0.660	-0.097	-0.037
$\Delta INVACC_{t+1}$	-0.312	0.488	0.200	-0.336	-0.560	-	0.144	0.072
ΔINC_{t+1}	-0.166	0.221	-0.106	0.397	-0.145	0.176	-	0.178
RET_{t+1}	-0.031	0.080	0.167	0.118	-0.028	0.080	0.306	-

For inclusion in the sample firms must be non-financial domestic firms and have the necessary data to compute accruals and cash flows in year t and t+1 and a return in year t+1 resulting in a base sample of 151,157 firm-year observations. All correlations are significant at less than the .001 percent level. Accruals, cash flows, inventory accruals and income are defined as follows:

Accruals (ACC_t) = Change in current assets (ACT) – change in cash (CHE) – change in current liabilities (LCT) + change in debt in current liabilities (DLC) + change in income taxes payable (TXP) scaled by average total assets (AT).

Cash Flows (CF_t) = Income (OIADP) minus accruals scaled by average total assets (AT).

Inventory Accruals ($INVACC_t$) = Change in inventory (INVT) scaled by average total assets (AT).
Change in Income (ΔINC_{t+1}) = Change in income (OIADP) scaled by average total assets (AT).
ΔCF_{t+1}, ΔACC_{t+1} and $\Delta INVACC_{t+1,}$ are all measured as the year over year change in cash flows, accruals and inventory accrual from period t to t+1. ACC, CF, INVACC, ABACC, NORMACC and ΔINC are winsorised at +/-1. RET_{t+1} is the annual buy-hold stock return. It is measured using compounded monthly returns, inclusive of dividends and other distributions. Returns are calculated for a twelve-month period beginning four months after fiscal year end.

Table 2
Distribution of firm-years across consecutive annual quintile rankings for periods t and t+1

Panel A: Ranking on Earnings (INC)

t+1 / *t*	*Bottom*	*2*	*3*	*4*	*Top*
Bottom	14.28%**	3.86%	0.99%**	0.48%**	0.38%**
2	3.53%**	9.82%**	4.77%**	1.36%**	0.53%**
3	1.08%**	4.00%	9.34%**	4.71%**	0.89%**
4	0.61%**	1.56%**	3.80%**	10.32%**	3.72%**
Top	0.50%**	0.77%**	1.11%**	3.14%**	14.48%**

Panel B: Ranking on Cash Flows (CF)

t+1 / *t*	*Bottom*	*2*	*3*	*4*	*Top*
Bottom	11.52%**	3.76%	1.82%**	1.31%**	1.58%**
2	3.80%	6.98%**	4.51%**	2.76%**	1.96%**
3	1.86%**	4.57%**	6.64%**	4.69%**	2.25%**
4	1.33%**	2.81%**	4.74%**	7.14%**	3.99%
Top	1.48%**	1.88%**	2.31%**	4.11%	10.22%**

Panel C: Ranking on Accruals (ACC)

t+1 / *t*	*Bottom*	*2*	*3*	*4*	*Top*
Bottom	5.46%**	3.41%**	2.94%**	3.55%**	4.62%**
2	3.15%**	5.24%**	5.25%**	3.91%	2.46%**
3	2.72%**	4.96%**	5.58%**	4.24%**	2.51%**
4	3.56%**	3.89%	3.97%**	4.73%**	3.86%
Top	5.10%**	2.51%**	2.26%**	3.58%**	6.55%**

Panel D: Ranking on Inventory Accruals (INVACC)

t+1 / *t*	*Bottom*	*2*	*3*	*4*	*Top*
Bottom	6.31%**	3.01%**	2.50%**	3.89%	4.35%
2	1.85%**	8.37%**	6.65%**	2.76%**	1.50%**
3	1.97%**	4.54%	6.93%**	3.67%	1.76%**
4	4.15%	2.87%**	2.70%**	5.75%**	4.45%**
Top	5.69%**	1.47%**	1.21%**	3.70%*	7.94%**

**, * Frequency is statistically different from 4% at the 1% or 5% levels respectively.
Cells with frequency>4% are shaded.
Significance is calculated using t-statistics based on annual time-series means and the standard error of the annual time-series means. These tables present transition frequencies for earnings, cash flows, accruals and inventory accruals. For inclusion in the sample firms must be non-financial domestic firms and have the necessary data to compute accruals and cash flows in year t and t+1 and a return in year t+1 resulting in a base sample of 151,157 firm-year observations from 1962-2007. Quintile rankings are constructed for each variable in fiscal year t and again in fiscal year t+1. The rows correspond to the ranking in fiscal year t and the columns to t+1. Each cell reports the percentage of the sample falling into that particular combination of rankings in the two adjacent years.

Table 3
Mean period t+1 change in accruals, earnings and buy and hold returns for consecutive annual quintile accrual rankings (Firm years from 1962-2007)

Panel A: Mean Change in Accruals (ΔACC_{t+1}) by Consecutive Annual Accrual Rankings

t+1 / *t*	*Bottom*	*2*	*3*	*4*	*Top*	*Row Mean*
Bottom	-0.023	0.070	0.094	0.135	0.302	0.114
2	-0.084	-0.003	0.022	0.055	0.145	0.020
3	-0.114	-0.029	-0.003	0.028	0.112	-0.003
4	-0.156	-0.065	-0.035	-0.005	0.079	-0.033
Top	-0.336	-0.165	-0.128	-0.098	-0.016	-0.144

Panel B: Mean Change in Inventory Accruals ($\Delta INVACC_{t+1}$) by Consecutive Annual Inventory Accrual Rankings

t+1 / *t*	*Bottom*	*2*	*3*	*4*	*Top*	*Row Mean*
Bottom	-0.007	0.037	0.049	0.068	0.164	0.058
2	-0.035	0.000	0.004	0.025	0.099	0.009
3	-0.053	-0.008	0.000	0.015	0.084	0.003
4	-0.079	-0.031	-0.018	-0.002	0.056	-0.012
Top	-0.204	-0.105	-0.092	-0.067	-0.007	-0.087

Panel C: Mean Change in Earnings (ΔINC_{t+1}) by Consecutive Annual Accrual Rankings

t+1 / *T*	*Bottom*	*2*	*3*	*4*	*Top*	*Row Mean*
Bottom	-0.018	0.015	0.014	0.021	0.056	0.016
2	-0.030	-0.005	-0.001	0.002	0.016	-0.004
3	-0.038	-0.009	-0.003	-0.001	0.004	-0.008
4	-0.048	-0.014	-0.009	-0.004	0.004	-0.013
Top	-0.082	-0.032	-0.027	-0.016	-0.007	-0.033

Panel D: Mean Change in Earnings (ΔINC_{t+1}) by Consecutive Annual Inventory Accrual Rankings

t+1 / *T*	*Bottom*	*2*	*3*	*4*	*Top*	*Row Mean*
Bottom	-0.004	0.008	0.011	0.016	0.025	0.010
2	-0.016	-0.009	-0.010	-0.002	0.002	-0.008
3	-0.020	-0.007	-0.003	-0.004	0.004	-0.005
4	-0.028	-0.015	-0.009	-0.007	-0.004	-0.012
Top	-0.052	-0.030	-0.019	-0.018	-0.014	-0.027

Panel E: Mean Buy-hold Returns (RET_{t+1}) by Consecutive Annual Accrual Rankings

t+1 / *t*	*Bottom*	*2*	*3*	*4*	*Top*	*Row Mean*
Bottom	0.101	0.182	0.198	0.187	0.249	0.178
2	0.111	0.150	0.174	0.158	0.222	0.161
3	0.115	0.138	0.145	0.168	0.219	0.153
4	0.059	0.133	0.136	0.152	0.206	0.139
Top	-0.007	0.088	0.068	0.100	0.196	0.099

Panel F: Mean Buy-hold Returns (RET_{t+1}) by Consecutive Annual Inventory Accrual Rankings

t+1 / *t*	*Bottom*	*2*	*3*	*4*	*Top*	*Row Mean*
Bottom	0.120	0.188	0.213	0.213	0.307	0.200
2	0.098	0.128	0.138	0.189	0.248	0.145
3	0.104	0.091	0.186	0.168	0.243	0.156
4	0.069	0.134	0.130	0.130	0.206	0.135
Top	-0.007	0.092	0.076	0.106	0.166	0.095

These tables present transition matrices of accruals and inventory accrual quintiles in fiscal year t to accrual and inventory accrual quintiles in fiscal year t+1. The rows correspond to current accruals and inventory accrual rankings and the columns correspond to future accrual and inventory accrual rankings. Accruals and inventory accruals are ranked on an annual basis. Panels A & B contain the mean period t+1 change in accruals and inventory accruals. Panels C & D contain the mean period t+1 change in income (OIADP) scaled by average total assets (AT). Panels E & F contain the mean period t+1 buy-hold return, RET_{t+1}. RET_{t+1} is the annual buy-hold stock return. It is measured using compounded monthly returns, inclusive of dividends and other distributions. Returns are calculated for a twelve-month period beginning four months after fiscal year end. Working capital and inventory accruals are scaled by average total assets. Accruals, changes in inventory and changes in income are winsorised at +/- 1.

Table 4
Pooled cross-sectional regressions of dummy variables for observations in extreme quintiles (Firm-years from 1962-2007)

Panel A: Income Regressions

Dependent Variables	Independent Variables			
	Intercept	$LINC_t$	$HINC_t$	Adj. R^2
$HINC_{t+1}$	0.0857	-0.067	0.638	0.433
	(46.19)	(-31.02)	(85.7)	
$LINC_{t+1}$	0.0875	0.627	-0.063	0.417
	(28.83)	(48.06)	(-24.95)	

Panel B: Cash Flow Regressions

	Intercept	LCF_t	HCF_t	Adj. R^2
HCF_{t+1}	0.137	-0.058	0.374	0.154
	(65.10)	(-10.63)	(39.19)	
LCF_{t+1}	0.117	0.460	-0.043	0.223
	(22.64)	(18.77)	(-13.89)	

Panel C: Accrual Regressions

	Intercept	$LACC_t$	$HACC_t$	Adj. R^2
$HACC_{t+1}$	0.147	0.084	0.181	0.032
	(74.69)	(14.07)	(23.11)	
$LACC_{t+1}$	0.158	0.116	0.098	0.017
	(74.95)	(22.78)	(13.7)	

Panel D: Inventory Accrual Regressions

	Intercept	$LINVACC_t$	$HINVACC_t$	Adj. R^2
$HINVACC_{t+1}$	0.129	0.088	0.268	0.068
	(41.34)	(11.13)	(29.63)	
$LINVACC_{t+1}$	0.133	0.182	0.152	0.042
	(35.16)	(16.76)	(14.28)	

The t-statistics (reported in parentheses below coefficient estimates) are calculated using the Gow, Ormazabal and Taylor (2007) correction for cross-sectional and time-series dependence. For inclusion in the sample firms must be non-financial firms and have the necessary data to calculate accruals and cash flows in year t and t+1 and a return in year t+1 resulting in a base sample of 151,157 firm-year observations.

Variables are defined as follows:

INC_t =Income (OIADP) scaled by average total assets (AT).

Accruals (ACC_t) =Change in current assets (ACT) – change in cash (CHE) – change in current liabilities (LCT) + change in debt in current liabilities (DLC) + change in income taxes payable (TXP) scaled by average total assets (AT).

Cash Flows (CF_t) =Income (OIADP) minus accruals scaled by average total assets (AT).

Inventory Accruals ($INVACC_t$) = Change in inventory (INVT) scaled by average total assets (AT). $LINC_t$, LCF_t, LINC, LCF, LACC, and LINVACC, are dummy variables taking the value of 1 for firms in the lowest quintile of INC, CF, ACC and INVACC respectively. HINC, HCF, HACC, and HINVACC, are dummy variables taking the value of 1 for firms in the highest quintile of INC, CF, ACC and INVACC respectively. Otherwise, all dummy variables default to zero.

Table 5
Pooled cross-sectional auto-regressions including interactions with dummy variables for extreme accrual reversals (Firm-years from 1962-2007)

Panel A: Income Regressions

Dependent Variables	Independent Variables				
	Intercept	INC_t	$INC*HLINC_{t+1}$	$INC*LHINC_{t+1}$	Adj. R^2
INC_{t+1}	-0.001	0.841			
	(-0.24)	(92.83)			0.697
INC_{t+1}	-0.001	0.865	-1.405	-1.423	
	(-0.51)	(103.85)	(-23.78)	(-32.79)	0.731

Panel B: Cash Flow Regressions

	Intercept	CF_t	$CF*HLCF_{t+1}$	$CF*LHCF_{t+1}$	Adj. R^2
CF_{t+1}	0.009	0.679			
	(3.11)	(39.56)			0.470
CF_{t+1}	0.008	0.761	-1.394	-1.503	
	(3.06)	(60.33)	(-34.77)	(-52.79)	0.585

Panel C: Accrual Regressions

	Intercept	ACC_t	$ACC*HLACC_{t+1}$	$ACC*LHACC_{t+1}$	Adj. R^2
ACC_{t+1}	0.012	0.025			
	(5.35)	(2.08)			0.001
ACC_{t+1}	0.006	0.397	-1.099	-1.160	
	(3.35)	(53.91)	(-62.49)	(-78.63)	0.274

Panel D: Inventory Accrual Regressions

	Intercept	$INVACC_t$	$INVACC*HLINVACC_{t+1}$	$INVACC*LHINVACC_{t+1}$	Adj. R^2
$INVACC_{t+1}$	0.011	0.120			
	(6.88)	(9.20)			0.014
$INVACC_{t+1}$	0.008	0.448	-1.023	-1.232	
	(6.12)	(37.15)	(-61.59)	(-49.52)	0.266

The t-statistics (reported in parentheses below coefficient estimates) are calculated using the Gow, Ormazabal and Taylor (2007) correction for cross-sectional and time-series dependence. For inclusion in the sample firms must be non-financial firms and have the necessary data to calculate accruals and cash flows in year t and t+1 and a return in year t+1 resulting in a base sample of 151,157 firm-year observations. Accruals, cash flows and changes in inventory are defined as follows:

INC_t	=Income (OIADP) scaled by average total assets (AT).
Accruals (ACC_t)	=Change in current assets (ACT) – change in cash (CHE) – change in current liabilities (LCT) + change in debt in current liabilities (DLC) + change in income taxes payable (TXP) scaled by average total assets (AT).
Cash Flows (CF_t)	=Income (OIADP) minus accruals scaled by average total assets (AT).

Inventory Accruals ($INVACC_t$) = Change in inventory (INVT) scaled by average total assets (AT).p

$HLINC_{t+1}$, $HLACC_{t+1}$, $HLCF_{t+1}$, and $HLINVACC_{t+1}$, are dummy variables taking the value of 1 for firms moving from the highest quintile to the lowest quintile of INC, ACC, CF and ΔINV respectively between period t and t+1. $LHINC_{t+1}$, $LHACC_{t+1}$, $LHCF_{t+1}$, and $LHINVACC_{t+1}$, are dummy variables taking the value of 1 for firms moving from the lowest quintile to the highest quintile of INC, ACC, CF and INVACC respectively between period t and t+1. Otherwise, all dummy variables default to zero. INC, ACC, CF and ΔINV are winsorised at +/-1.

Table 6
Pooled cross-sectional regressions of next period income on accruals, change in accruals, and change in cash flows (Firm-years from 1962-2007)

Dependent Variables	Independent Variables					
	Intercept	CF_t	ACC_t	ΔACC_{t+1}	ΔCF_{t+1}	Adj. R^2
ΔINC_{t+1}	0.000	-0.135	-0.246			0.063
	(0.11)	(-11.33)	(-18.76)			
ΔINC_{t+1}	-0.002	-0.160	0.019	0.286		0.124
	(-1.04)	(-12.83)	(1.08)	(20.09)		
ΔINC_{t+1}	0.004	-0.014	-0.568		0.537	0.370
	(2.24)	(-1.56)	(-32.53)		(27.79)	

The t-statistics (reported in parentheses below coefficient estimates) are calculated using the Gow, Ormazabal and Taylor (2007) correction for cross-sectional and time-series dependence. For inclusion in the sample firms must be non-financial domestic firms and have the necessary data to calculate accruals and cash flows in year t and t+1 and a return in year t+1 resulting in a base sample of 151,157 firm-year observations
INC_{t+1} is the next period income (item OIADP) scaled by average total assets (AT).
ACC_t, , CF_t are defined as follows:

Accruals (ACC_t)	=change in current assets (ACT) – change in cash (CHE) – change in current liabilities (LCT) + change in debt in current liabilities (DLC) + change in income taxes payable (TXP) scaled by average total assets (AT).
Cash Flows (CF_t)	=Income (OIADP) minus accruals scaled by average total assets (AT).

ΔACC_{t+1}, ΔCF_{t+1} are all measured as the year over year change in accruals and inventory from period t to t+1. ΔINC, ACC and CF are winsorised at +/- 1.

Table 7
Pooled cross-sectional regressions of buy-hold returns on accruals, change in cash flows, change in income and change in accruals (Firm-years from 1962-2007)

Dependent Variables	Independent Variables									
	Intercept	ACC_t	ΔCF_{t+1}	ΔINC_{t+1}	ΔACC_{t+1}	BM	SIZE	MOM6	MOM36	Adj. R^2
RET_{t+1}	0.563	-0.178				0.026	-0.024	0.025	-0.011	0.007
	(3.33)	(-2.25)				(1.20)	(-2.83)	(0.60)	(-1.17)	
RET_{t+1}	0.546	0.012		1.134		0.031	-0.023	0.001	-0.007	0.038
	(3.21)	(0.14)		(12.32)		(1.42)	(-2.70)	(0.01)	(-0.77)	
RET_{t+1}	0.548	0.348			0.532	0.033	-0.023	0.017	-0.014	0.012
	(3.25)	(2.80)			(8.64)	(1.50)	(-2.81)	(0.43)	(-1.52)	
RET_{t+1}	0.568	-0.625	0.604			0.021	-0.023	0.020	-0.006	0.017
	(3.36)	(-5.82)	(9.04)			(0.99)	(-2.80)	(0.49)	(-0.63)	

The t-statistics (reported in parentheses below coefficient estimates) are calculated using the Gow, Ormazabal and Taylor (2007) correction for cross-sectional and time-series dependence. For inclusion in the sample firms must be non-financial domestic firms and have the necessary data to calculate accruals and cash flows in year t and t+1 and a return in year t+1 resulting in a base sample of 151,157 firm-year observations
RET_{t+1} is the annual buy-hold stock return. It is measured using compounded monthly returns, inclusive of dividends and other distributions. Returns are calculated for a twelve-month period beginning four months after fiscal year end.

The independent variables are defined as follows:

ΔINC_{t+1}	=year over year change in Income (OIADP) scaled by average total assets (AT).
Accruals (ACC_t)	= change in current assets (ACT) – change in cash (CHE) – change in current liabilities (LCT) + change in debt in current liabilities (DLC) + change in income taxes payable (TXP) scaled by average total assets (AT).
Cash Flows (CF_t)	=Income (OIADP) minus accruals scaled by average total assets (AT).
BM	=Book value of equity at the end of the prior fiscal year scaled by market value of equity at the end of the prior fiscal year
SIZE	=Natural log of market value of equity in the month prior to the compounding of RET_{t+1}
MOM6	=6 month compound return for the six months preceding RET_{t+1}
MOM36	=36 month compound return for the 36 months preceding RET_{t+1}

ΔACC_{t+1}, and ΔCF_{t+1} are measured as the year over year change in accruals and cash flows from period t to t+1. ΔINC_{t+1}, ACC and CF are winsorised at +/- 1

Table 8
Transition matrices and regressions for normal and abnormal accruals
(Firm-years from 1962-2007)

Panel A: Normal and Abnormal Accrual Transition Matrices

Normal Accruals t and Accruals t+1

t \ t+1	Bottom	2	3	4	Top
Bottom	6.54%	4.00%	2.98%	3.05%	3.42%
2	3.48%	5.64%	5.44%	3.40%	2.04%
3	3.03%	4.60%	5.36%	4.38%	2.63%
4	3.24%	3.48%	3.87%	5.15%	4.27%
Top	3.69%	2.29%	2.35%	4.02%	7.63%

Abnormal Accruals t and Accruals t+1

t \ t+1	Bottom	2	3	4	Top
Bottom	4.53%	2.92%	2.71%	3.87%	5.95%
2	3.18%	4.19%	4.62%	4.57%	3.44%
3	2.56%	5.20%	5.76%	4.05%	2.44%
4	3.54%	4.68%	4.36%	4.17%	3.26%
Top	6.17%	3.02%	2.55%	3.35%	4.90%

Panel B: Extreme Quintile Regressions

Dependent Variables	Independent Variables					
	Intercept	$LNORMACC_t$	$HNORMACC_t$	$LABACC_t$	$HABACC_t$	Adj. R^2
$HACC_{t+1}$	0.1246	0.0034	0.2053	0.0888	0.0809	0.062
	(61.72)	(0.86)	(27.48)	(20.38)	(17.05)	
$LACC_{t+1}$	0.1325	0.1367	-0.0016	0.0717	0.1274	0.042
	(53.99)	(24.52)	(-0.28)	(16.59)	(27.39)	

Panel C: Income Regressions

	Intercept	$HACC_t$-$LACC_t$	$HABACC_t$-$LABACC_t$	$HNORMACC_t$-$LNORMACC_t$	Adj. R^2
ΔINC_{t+1}	-0.008	-0.025			0.015
	(-5.17)	(-17.14)			
ΔINC_{t+1}	-0.008		-0.020	-0.020	0.016
	(-5.17)		(-20.07)	(-13.17)	

Panel D: Return Regressions

	Intercept	$HACC_t$-$LACC_t$	$HABACC_t$-$LABACC_t$	$HNORMACC_t$-$LNORMACC_t$	BM	SIZE	MOM6	MOM36	Adj. R^2
RET_{t+1}	0.557	-0.034			0.025	-0.023	0.024	-0.011	0.007
	(3.32)	(-3.19)			(1.13)	(-2.81)	(0.59)	(-1.16)	
RET_{t+1}	0.556		-0.036	-0.005	0.027	-0.023	0.024	-0.012	0.008
	(3.31)		(-6.07)	(-0.46)	(1.19)	(-2.81)	(0.60)	(-1.25)	

Cells with frequency>4% are shaded.

The t-statistics (reported in parentheses below coefficient estimates) are calculated using the Gow, Ormazabal and Taylor (2007) correction for cross-sectional and time-series dependence. For inclusion in the sample firms must be non-financial domestic firms and have the necessary data to calculate accruals and cash flows in year t and t+1 and a return in year t+1. We also require for this table positive sales in periods t and t-1 to calculate normal and abnormal accruals resulting in a base sample of 147,818 firm-year observations. RET_{t+1} is the annual buy-hold stock return. It is measured using compounded monthly returns, inclusive of dividends and other distributions. Returns are calculated for a twelve-month period beginning four months after fiscal year end. The other dependent and independent variables are defined as follows:

ΔINC_{t+1}	=year over year change in Income (OIADP) scaled by average total assets (AT).
Accruals (ACC_t)	= change in current assets (ACT) – change in cash (CHE) – change in current liabilities (LCT) + change in debt in current liabilities (DLC) + change in income taxes payable (TXP) scaled by average total assets (AT).
BM	=Book value of equity at the end of the prior fiscal year scaled by market value of equity at the end of the prior fiscal year
SIZE	=Natural log of market value of equity in the month prior to the compounding of RET_{t+1}
MOM6	=6 month compound return for the six months preceding RET_{t+1}
MOM36	=36 month compound return for the 36 months preceding RET_{t+1}

Normal accruals ($NORMACC_t$) is measured as $(SALES_t/SALES_{t-1})*WC_{t-1}-WC_{t-1}$. Abnormal Accruals ($ABACC_t$) is the difference between actual accruals and normal accruals. WC is defined as current assets (ACT) – cash (CHE) – current liabilities (LCT) + debt in current liabilities (DLC) + income taxes payable (TXP). Accruals and normal and abnormal accruals are sorted into quintiles. For accruals falling into the highest (lowest) quintile of accruals and normal and abnormal accruals $HACC_t$ ($LACC_t$), $HNORMACC_t$ ($LNORMACC_t$) and $HABACC_t$ ($LABACC_t$) respectively are set equal to 1 and 0 otherwise. Accruals in t+1 are also sorted into quintiles and $HACC_{t+1}$ ($LACC_{t+1}$) equals one if firms fall in the highest (lowest) quintile of accruals and 0 otherwise. ΔINC is winsorised at +/-1.

Table 9
Descriptive statistics and pair-wise correlations for firms experiencing inventory write-downs (From 2001-2004)

Panel A: Descriptive Statistics

	Mean	25%	Median	75%
Average Total Assets ($Mill.)	1380.990	52.547	196.897	661.259
INC	-0.061	-0.145	0.008	0.082
INVACC	-0.018	-0.042	-0.006	0.017
ΔINVACC	-0.024	-0.057	-0.007	0.026
Inventory Write-Down ($Mill.)	11.103	-6.600	-1.900	-0.527
WD	-0.025	-0.026	-0.010	-0.004

Panel B: Pair-wise correlations - Pearson (above diagonal) and Spearman (below diagonal)

	WD_{t+1}	$INVACC_t$	$INVACC_{t+1}$	$\Delta INVACC_{t+1}$	ΔINC_t	ΔINC_{t+1}
WD_{t+1}	-	-0.082	0.383	0.346	0.021	0.269
		0.000	0.000	0.000	0.354	0.000
$INVACC_t$	-0.076	-	0.010	-0.645	0.161	-0.167
	0.001		0.675	0.000	0.000	0.000
$INVACC_{t+1}$	0.3408	0.0355	-	0.758	0.128	0.238
	0.000	0.125		0.000	0.000	0.000
$\Delta INVACC_{t+1}$	0.272	-0.609	0.660	-	-0.007	0.291
	0.000	0.000	0.000		0.775	0.000
ΔINC_t	0.092	0.160	0.186	0.030	-	-0.009
	0.000	0.000	0.000	0.203		0.688
ΔINC_{t+1}	0.295	-0.259	0.207	0.334	-0.005	-
	0.000	0.000	0.000	0.000	0.815	

To create this sample we searched all 10-K filings on DirectEdgar for inventory write-downs during the calendar years 2001 through 2004. We began by taking all firms that were listed on the CRSP and COMPUSTAT databases during the period from January 1, 2000 through December 31, 2004, and eliminating all firms whose exchange code indicated they were not listed on the NASDAQ, NYSE, or AMEX stock exchanges four months after their fiscal year end. We then conduct a keyword search for any form of write within ten words of inventory and read items one through seven of each 10-K for discussion or documentation of an inventory write-down during the current fiscal year. Upon finding evidence of an inventory write-down, we collected the inventory write-down amount from the annual report. After data restrictions, our final sample consists of 1,869 firm-year observations. WD is the inventory write-down scaled by average total assets. Income and inventory accruals are defined as follows:

Change in Current Period income (ΔINC_t)	= Change in income (OIADP) scaled by average total assets (AT).
Inventory Accruals ($INVACC_t$)	= Change in inventory (INVT) scaled by average total assets (AT).
Inventory Accrual Reversal ($\Delta INVACC_t$)	= difference between changes in inventory from period t to t+1

WD, INVACC and ΔINVACC are winsorised at +/-1

Table 10
Distribution of firms-years across inventory accrual quintiles for period's t and t+1 and inventory write-down statistics for period t (Firm years from 2001-2004)

t+1 *t*	*Bottom*	*2*	*3*	*4*	*5*	*Row Mean*
Bottom						
% of the Entire Sample	7.25	3.31	0.98	3.34	5.12	
% of WD Firms$_{t+1}$	17.07	3.53	1.12	4.07	7.92	
Avg. WD$_{t+1}$	-0.037**	-0.009**	-0.012**	-0.024	-0.014**	-0.026**
2						
	2.12	3.92	8.30	4.00	2.41	
	3.21	3.32	0.70	2.09	2.09	
	-0.021**	-0.006**	-0.002**	-0.006**	-0.009**	-0.011**
3						
	0.39	5.98	10.90	1.80	0.79	
	0.54	0.59	0.43	0.70	0.70	
	-0.018**	-0.011**	-0.008*	-0.005*	-0.038*	-0.017**
4						
	3.46	4.16	1.79	5.96	4.03	
	6.63	3.37	0.75	3.37	3.58	
	-0.029**	-0.009**	-0.006**	-0.011**	-0.015**	-0.018**
5						
	6.77	2.04	0.40	3.12	7.66	
	16.16	3.21	0.64	4.12	10.11	
	-0.048**	-0.020**	-0.011	-0.014**	-0.027**	-0.034**

This table presents the distribution of firm-year inventory accrual quintiles in calendar years t and t+1. The first row is the percentage of firm-years from the entire sample of 15,342 firm years from calendar years 2001-2004. The second row is the percentage of the 1,869 inventory write-down firm years with available data that fell in the corresponding inventory accrual quintiles in calendar years t and t+1. The third row is the average scaled inventory write-down in period t+1 (WD) for inventory write-down firm years falling in each cell. WD is winsorised at +/-1.
*,** represent p-values at the 5% and 1% levels respectively.
Cells with frequency>4% are shaded.

Table 11
Cross-sectional pooled regressions of period t+1 inventory write-downs on previous period inventory accruals and related explanatory variables (Firm-years from 2001-2004)

	Intercept	$INVACC_t$	$INVACC_t$ * $HINVACC_t$	$INVACC_{t-1}$	$INVACC_{t-1}$ * $HINVACC_{t-1}$	ACC_t- $INVACC_t$	CF_{t-1}	INV_{t-1}	INV_{t-2}	Adj. R^2
WD_{t+1}	-0.001	0.027	-0.073			0.006	0.007	-0.011		0.026
	(-1.98)	(2.44)	(-5.15)			(6.77)	(4.90)	(-3.92)		
WD_{t+1}	-0.001	0.026	-0.070	0.007	-0.028	0.006	0.007		-0.008	0.027
	(-2.73)	(2.55)	(-6.58)	(0.78)	(-2.74)	(5.04)	(6.15)		(-3.18)	

The t-statistics (reported in parentheses below coefficient estimates) are calculated using the Gow, Ormazabal and Taylor (2007) correction for cross-sectional and time-series dependence. We include in the sample all non-financial firm year observations in calendar years 2001 through 2004 with the necessary data to calculate accruals and cash flows and changes in inventory in year t-1 and t and a return in year t resulting in a base sample of 15,342 firm-year observations. Each individual regression is estimated with all observations with available data. The variables are defined as follows:

Accruals (ACC_t)	=Change in current assets (ACT) – change in cash (CHE) – change in current liabilities (LCT) + change in debt in current liabilities (DLC) + change in income taxes payable (TXP) scaled by average total assets (AT).
Cash Flows (CF_t)	=Income (OIADP) minus accruals scaled by average total assets (AT).
Inventory (INV)	= inventory (INVT) scaled by total assets (AT).
Inventory Accruals ($INVACC_t$)	= Change in inventory (INVT) scaled by average total assets (AT).
Inventory Writedown (WD_t)	= Hand collected inventory write-down amount scaled by average total assets (AT).
HINVACC	=Indicator variable equal to 1 if a firm is in the highest quintile of changes in inventory and 0 otherwise.

INVACC, INV, WD, ACC and CF are winsorised at +/-1.