Impairment Write-Offs and the Pricing of Accruals

HENRY JARVA*

University of Oulu, Department of Accounting and Finance
P.O. Box 4600, FIN–90014 University of Oulu, Finland.

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***Contact Address:** Henry Jarva, Department of Accounting and Finance, University of Oulu, P.O. Box 4600, FIN–90014 University of Oulu, Finland. Phone: (+358) 8 553 2928; fax: (+358) 8 553 2906; e-mail: henry.jarva@oulu.fi.

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Impairment Write-Offs and the Pricing of Accruals

Abstract

Sloan (1996) is the first to document the accruals anomaly, the negative relation between accruals and subsequent stock returns. In this paper I investigate the effects of the recent and prominent adoption of fair-value accounting on the market valuation of accruals. Using a sample of firm-years from 2003 to 2005, I find that investors rationally price different earnings components when setting prices. Further analysis confirms that there are no significant differences in future returns between impairment write-off and control sample firms. These results are inconsistent with the earnings fixation hypothesis proposed by Sloan (1996). I conjecture that recent adoption of fair-value accounting does not contribute to the accruals anomaly.

JEL classification: G10, M4

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Data availability: All data are available from public sources.

1. Introduction

Sloan (1996) is the first to document the negative association between accounting accruals and subsequent stock returns.[1] The finding that low (high) accrual firms earn higher (lower) returns, given their risk, is known as the accruals anomaly. Sloan (1996) argues that investors naively fixate on earnings and fail to identify correctly the different properties of the accrual and cash flow components of earnings. Subsequent research has not reached consensus on the explanation for the accruals anomaly.

One stream of literature examines whether certain components of earnings are mispriced (Xie, 2001; Thomas and Zhang, 2002; Richardson et al., 2005; Dechow and Ge, 2006; Dechow et al., 2008). A second stream examines the relationship between the accruals anomaly and other previously know anomaly (Collins and Hribar, 2000; Desai et al. 2004; Fairfield et al., 2003; Zhang, 2007). A third stream investigates whether the valuation implications of accruals are reflected by insiders and sophisticated investors (Bradshaw et al., Beneish and Vargus, 2002, 2001; Collins et al., 2003; Core et al., 2006; Lev and Nissim, 2006). A fourth stream explores whether accruals are mispriced in other countries (LaFond, 2005; Pincus et al., 2007; Kaserer and Klingler, 2008). Finally, a fifth stream of research proposes a risk based explanation for the accrual anomaly, and address research design issues (Khan, 2008a, 2008b; Mashruwala et al., 2006; Kraft et al., 2006, 2007).

In this paper I investigate the effects of the recent and prominent adoption of fair-value accounting on the market valuation of accruals. Specifically, I examine whether impairment write-offs and concurrent abnormal accruals are associated with future stock

[1] Sloan (1996) is very influential study in accounting. As of 29 April 2008, 746 citations are recorded on Google Scholar (http://scholar.google.com).

returns. Evidence in Dechow and Ge (2006) suggest that accounting conservatism contributes to the accruals anomaly.[2] Further, Richardson et al. (2005) suggest that there are significant costs associated with incorporating less reliable accrual information in financial statements. Opponents of fair value accounting argue that relative noisy (e.g., unverifiable fair-value estimates) accruals weaken the accounting earnings ability to predict future cash flows and hence firm value. Under fair-value accounting assets and liabilities embody expected future inflows and outflows of future benefits. By definition, gain and loss accruals should incorporate information about changes in expected future cash flows. By examining unverifiable loss recognition accruals, I provide evidence whether the recent adoption of fair-value accounting contributes to the accruals anomaly.

The Financial Accounting Standards Board (FASB) has recently signaled a fundamental conceptual shift towards the broad-based adoption of fair-value accounting. Accordingly, assets and liabilities are measured at fair-values, albeit in an asymmetrical fashion.[3] When fair-value estimates are based on market values, they are likely to be verifiable (Holthausen and Watts, 2001). Unverifiability arises when quoted market values of for assets and liabilities are not available. In this case, assessing fair-values require managers to estimate future cash inflows and outflows. Watts (2003) argue that because those estimates are unlikely to be verifiable and contractible, they, and valuation based on them, are likely to be manipulated. In addition, earnings based on fair-values incorporate estimates of future events, but managers rarely report the precision of those estimates. The information-processing costs and risks associated with unverifiable fair-value estimates are likely to be non-trivial and may affect asset prices.

[2] Specifically, they show that low accrual firms with special items have higher future stock returns than other low accrual firms.
[3] See Basu (1997) and Ball and Shivakumar (2006).

A key problem in investigating the relationship between impairment write-offs and subsequent stock returns is determining how these firms would have performed had they not done the write-off. It is well known that accruals are correlated with a firm's contemporaneous and past performance (e.g., Dechow et al., 1998). Fama (1970) noted that tests of market efficiency are joint tests of efficiency and a model of specifying expected returns. The problem with any observed market inefficiency is that it may be due to mismeasured risk if the benchmark pricing model is not empirically descriptive (Ball, 1978). A common approach is to use some type of risk adjustment (e.g., size-adjusted returns) and include additional variables that are associated with returns. Another common approach is to use a matched sample design. Since not all firms report write-offs I choose to control for confounding factors through a matched sample design.

I find that investors rationally price different earnings components when setting prices. Specifically, I do not find evidence that impairment write-offs are associated with abnormal future returns. These results are inconsistent with the earnings fixation hypothesis proposed by Sloan (1996). I suggest that concerns about fair-value accounting leading to significant security mispricing are not warranted.

The findings have implications for future research. First, the findings in this study suggest that Sloan's (1996) earnings fixation hypothesis is unlikely to be large in magnitude in current accounting regime. Second, I conjecture that recent adoption of fair-value accounting has not led to significant security mispricing. Finally, I suggest the use of propensity score matching to control for selection bias especially in cases where there is relatively few firms that experience an event and a wider pool of control firms.

In what follows, Section 2 describes sample selection, measurement of variables, and descriptive statistics. Section 3 provides the results of traditional pricing tests. Section 4 describes the propensity score matching method. Section 5 presents the results of the propensity score matching. Section 6 concludes.

2. Sample selection, measurement of variables, and descriptive statistics

2.1. Sample selection

The sample comprises all firms listed on the New York (NYSE), American (AMEX), and NASDAQ markets for which requisite financial and return data are available over the period 2003–2006. Foreign companies are excluded. Empirical tests employ data from three sources. Financial statement data are obtained from the Worldscope database, stock return data are obtained from the Datastream, and analyst data are obtained from the I/B/E/S research files. Fair-value based accounting standards, SFAS 142 and SFAS 144, were effective in fiscal years beginning after December 15, 2001. As in Ramanna and Watts (2007), I exclude year 2002 because it is the initial adoption year for most firms.[4]

Stock returns are calculated from the Datastream return index. I download daily data for all firms and create annual returns from end-of-month daily data. Annual returns are for 12-month period beginning 3 months after the end of the fiscal year. If a firm delists during the return window, the return is calculated to the last trading day. The size-

[4] Beatty and Weber (2006) examine SFAS 142 adoption decisions, focusing on the trade-off between recording certain current goodwill impairment charges below the line and uncertain future impairment charges included in income from continuing operations. They find that both contracting and market incentives affect firms' accounting choices relating to the trade-off between the timing and presentation of expense recognition on income statements.

adjusted return is calculated by deducting the equally-weighted average return for firms in the same size-matched decile, where size is measured as the market value at the beginning of the return cumulation period. Consequently, this procedure yields a sample mean size-adjusted return measure that is identically zero.

Table 1 presents the sample selection criteria. The sample selection begins with the 13,035 firm-year observations included in the Worldscope and Datastream with non-missing lagged cash flow (CF_{t-1}), lagged market value of equity ($Size_{t-1}$), change in sales ($\Delta Sales_t$), earnings (E_t), cash flows (CF_t), market value of equity ($Size_t$), market-to-book ratio (MTB_t), and annual returns (R_t) over the period 2003–2006. Earnings and cash flow from operations are taken from the cash flow statement. Both variables are scaled by market value of equity ($Size_{t-1}$), which is measured three months after the fiscal year-end of year *t-1*. Firms in the financial services, insurance, and real estate industries (SIC 6000–6999) are removed (1,089 firm-years). Firm-years with negative book value of equity are excluded (390 firm-years). Missing values of impairments are replaced with zero. Firms with positive total impairment values are deleted (23 firm-years). The empirical tests require future returns (R_{t+1}) for year *t+1*. This eliminates 2006 year's data and 3,059 observations, reducing the sample to 8,474. To minimize the effect of outliers, I delete the firm-year observations that are in the top and bottom one-half percent of the distributions of the earnings (E_t) or return (R_t) variables (158 firm-years). Finally, I delete observations with less than 15 observations in any industry-year cross-sections, where industries are classified by the first two digits of the SIC code. This eliminates 626 observations, leaving 7,690 observations in the sample.

(Insert Table 1 about here)

2.2. Estimation of discretionary accruals

Accruals (ACC_t) are calculated by subtracting operating cash flow from earnings before extraordinary items, both taken from the cash flow statement.[5] Pre-impairment accruals ($PreACC_t$) are calculated by subtracting impairment write-offs (WO_t) from accruals (ACC_t). Discretionary accruals are estimated using the cross-sectional variation of the Jones (1991) model, as modified by Dechow and Dichev (2002). The change in revenues controls for working capital requirements and gross property, plant, and equipment controls for depreciation. Current operating cash flows control for the negative correlation between contemporaneous accruals and operating cash flows (Dechow, 1994). Past operating accruals control for the positive correlation between current accruals and lagged operating cash flows (Dechow and Dichev, 2002). I do not estimate piecewise accruals models for total accruals as proposed by Ball and Shivakumar (2006), because loss recognition in accruals is subject to managerial discretion, which is the main interest of present study. By contrast, I take loss recognition accruals directly from reported numbers and subtract this amount from total accruals. The following model is estimated separately for each combination of two-digit SIC code and calendar year (firm subscripts omitted):

[5] Hribar and Collins (2002) show that merger and acquisition activities, foreign currency translations, and divestitures introduce significant measurement error into accruals estimated using the balance sheet approach.

$$PreACC_t = \alpha_0 + \alpha_1 \Delta Sales_t + \alpha_2 PPE_t + \alpha_3 CF_t + \alpha_4 CF_{t-1} + \varepsilon_t \quad (1)$$

where $\Delta Sales_t$ is the change in sales for firm *i* in year *t*; PPE_t is gross property, plant, and equipment; CF_t is cash flow from operations; and ε_t is the error term. All variables are standardized by lagged market value of equity in an attempt to reduce heteroskedasticity. Nondiscretionary accruals, $NACC_t$, is the fitted value from Eq. (1) and discretionary accruals, $DACC_t$, is the residual from Eq. (1).

Table 2 presents average coefficients, adjusted R^2 values and Fama-MacBeth (1973) *t*-statistics from annual cross-sectional regressions. Consistent with prior research, the mean coefficient on $\Delta Sales_t$ is positive, while the mean coefficient on PPE_t is negative. Consistent with Dechow and Dichev (2002) the mean coefficients on current and lagged cash flows are negative and positive, respectively. The mean adjusted R^2 is 67%.

(Insert Table 2 about here)

2.3. Descriptive statistics

Panel A of Table 3 provides descriptive statistics of the financial variables used in the analysis. All earnings variables are scaled by market value of equity. The mean (median) earnings amount is –0.008 (0.041), while mean (median) cash flow cash from operations is 0.074 (0.072). This difference leads to negative mean (median) accruals –0.082 (–0.041). Contrary to Xie (2001), results show that nondiscretionary accruals are more variable than discretionary accruals. Total impairments have a median value of 0.000. However, the mean is –0.010, and this suggests that the distributions of impairments are highly skewed.

(Insert Table 3 about here)

Panel B of Table 3 reports both Spearman and Pearson correlations. For ease of exposition, I discuss the Spearman correlations. Consistent with Dechow (1994), who proposes that accruals offset transitory cash flow effects, nondiscretionary accruals ($NACC_t$) are negatively related to cash flows (CF_t). There is a negative correlation between nondiscretionary and discretionary accruals ($DACC_t$), which can be interpreted as an evidence of management smoothing income. Impairment write-offs (WO_t) are positively correlated with current period returns (R_t). Current period returns (R_t) is negatively correlated with future returns (R_{t+1}).

3. Results of traditional pricing tests

I present results of traditional pricing tests in two sections. Section 3.1 replicates Sloan's (1996) result that the market appears to underweight (overweight) the cash flow (accrual) component of earnings. Section 3.2 reports the market pricing of impairment write-offs and discretionary accruals.

3.1. Replication of Sloan's (1996) result

The natural starting point for the analysis is to examine whether there exists a negative correlation between accruals and future stock returns, as documented by Sloan (1996). As in prior research (e.g., Sloan, 1996), I conduct test of market efficiency with respect to cash flows and accruals using the Mishkin (1983) test (hereafter MT). The MT is a nonlinear maximum likelihood estimation procedure with two equations, a linear forecasting equation and a pricing equation. The equations are estimated jointly and inferences are drawn comparing the weights in the forecasting equation with the weights placed in the pricing equation. As in Sloan (1996), the test of market efficiency with respect to cash flows and accruals is based on the following forecasting and pricing equations (firm subscripts omitted):

$$E_{t+1} = \gamma_0 + \gamma_1 CF_t + \gamma_t ACC_t + v_{t+1} \qquad (2a)$$

$$SAR_{t+1} = \beta(E_{t+1} - \gamma_0^* - \gamma_1^* CF_t - \gamma_2^* ACC_t) + \varepsilon_{t+1} \qquad (2b)$$

where E_{t+1} is earnings in year *t+1*, CF_t is cash flow from operations; ACC_t is accruals, SAR_{t+1} is size-adjusted return, and v_{t+1} and ε_{t+1} are the error terms. The market efficiency imposes the constrains $\gamma_1 = \gamma_1^*$ and $\gamma_2 = \gamma_2^*$.

Mishkin (1983) and Abel and Mishkin (1983) show that the two-equation system is numerically identical to a single equation than can be estimated using OLS. Kraft, Leone, and Wasley (2007) show that simple OLS offers several advantages over the MT in a typical accounting research setting. An important advantage of OLS is that it eliminates survivor bias induced by the MT where earnings in year *t+1* are required. Therefore, I also estimate the following OLS regression (firm subscripts omitted):

$$SAR_{t+1} = \phi_0 + \phi_1 CF_t + \phi_2 ACC_t + u_{t+1} \quad (3)$$

The MT results reported in Table 4 are consistent with the findings reported in Sloan (1996). The estimation of the system converges without imposing any convergence criteria. The market appears to underweight (overweight) the cash flow (accrual) component of earnings. Specifically, the coefficient on cash flows in the forecasting equation is 0.815, which is greater than that in the pricing equation, 0.411, while the coefficient on accruals in the forecasting equation is 0.614, which is less than that in the pricing equation, 0.788.

(Insert Table 4 about here)

Consistent with equivalence of OLS and the MT, results from the OLS estimation are similar those based on the MT above. Specifically, the coefficient on CF is 0.291 (t = 6.93, significant at the 1% level), which is evidence of underweighting. A significant positive coefficient implies that extreme positive (negative) cash flows in year t are followed by extreme positive (negative) returns in period $t+1$. The coefficient on accruals is –0.121 (t = –2.83, significant at the 1% level), which is consistent with the overweighting of accruals. Kraft, Leone, and Wasley (2007) show that the coefficient from OLS are related to the coefficients form the MT as follows, $\gamma_{OLS} = \beta(\gamma_k - \gamma_k^*)$, where γ_{OLS} is the OLS coefficient, β is the scalar on unexpected earnings in the MT's pricing equation, γ_k is the coefficient from the MT's pricing equation, and γ_k^* is the coefficient from the MT's pricing equation. Note that there are 72 observations less in the MT than in the OLS regression, consistent with the argument that the MT induce a selection bias in accounting setting.[6] As a result, I conduct subsequent tests of pricing of accrual components using OLS.

Figure 1 reports the average level of earnings and its components for each decile of accruals. Decile 1 contains firms with extreme negative accruals and decile 10 has firms with extreme positive accruals. Several interesting points emerge from this figure. The most positive cash flows are reported for low accrual firms (decile 1). However, earnings are negative due to large negative accrual adjustments. Just the opposite relationship between cash flows and accruals is for high accrual firms (decile 10). For these firms accruals "match" large negative cash flows so that earnings are positive. The magnitude of the discretionary accruals is largest for extreme accrual deciles. This is consistent with the view that accruals models are misspecified for firms with extreme performance. Alternatively managers manipulate earnings in these firms. Largest impairment write-offs are reported in deciles 1 and 2.

(Insert Figure 1 about here)

Table 5 provides various measures across accrual deciles. Panel A reports the amounts presented in Figure 1 more formally. Panel B provides evidence about the characteristics of firms in different accrual deciles. Interestingly, most variables appear to display either a concave or monotonic relation between accruals. The market value of equity ($Size_t$) and the market-to-book ratio (MTB_t) is lowest in the extreme accrual deciles, exhibiting a concave relation with accruals. Sales growth ($SalesGr_t$) is lowest (highest) for low (high) accrual firms. The proportion of losses ($Loss$) decreases almost

[6] See also Kothari, Sabino, and Zach (2005).

monotonically with accruals. Analyst coverage ($Coverage$) also reflects a concave pattern being lowest in the extreme accrual deciles. Only 62% (60%) of the low (high) accrual firms are followed by analysts compared to middle accrual quintile where coverage is over 80%. There is no clear pattern for year *t* stock returns across accrual deciles. Finally, the future size-adjusted return (SAR_{t+1}) is highest (lowest) for low (high) accrual firms.

(Insert Table 5 about here)

3.2. Accrual components and future returns

Next, I examine whether different accrual components continue to explain future returns after controlling for fixed industry effects. I use the same industry classification as in Barth, Beaver, and Landsman (1998). It is well known that residuals may be correlated across firms (see, Bernard 1987, Petersen 2008). To address cross-sectional correlation I use clustered standard errors (clustered by year). Specifically, I estimate the following regression (firm subscripts omitted).

$$SAR_{t+1} = \phi_0 + \phi_1 CF_t + \phi_2 NACC_t + \phi_3 DACC_t + \phi_4 WO_t + \textit{fixed effects} + u_{t+1} \qquad (4)$$

Table 6 presents the estimated results. Inconsistent with prior research and results in Table 4, the market appears to correctly weight different earnings components. The coefficients have the predicted sign, but they are statistically insignificant after taking account the cross-sectional dependence in stock returns and industry fixed effects. This result is consistent with Kraft, Leone, and Wasley (2007) argument that accounting researchers must be careful when using the MT to test the rational pricing of accounting numbers.

Thus far, inferences have been drawn by examining the correlation between future size-adjusted returns and continuous accruals variables. For example, Khan (2008) conduct accrual mispricing tests at the portfolio level. It is important to note that not all firms report impairment write-offs. It is possible to "throw the baby out with the bathwater" if our model is not empirically descriptive. To further extend the analysis of the effect of impairment write-offs, I turn to examine these firms using a matched-sample approach.

4. The matching method

4.1. The deficiency of traditional matching method

It is common in accounting research that sample firms are fundamentally different from other firms. The problem of selection bias arises from the use of non-random samples (Maddala, 1991). Taking the mean outcome of out-of-sample firms is problematic, since these firms usually differ.[7] The matching procedure is one possible solution to correct for sample selection bias due to observable differences between sample firms and comparison firms.[8] Its basic idea is to find from out-of-sample firms

[7] For example, Elliot and Shaw (1988) analyze the earnings performance and the return behavior of firms that report large write-offs relatively to industry control groups.
[8] Another standard remedy for this problem is Heckman's (1979) two-stage procedure. See Winship and Mare (1992) for discussion of Heckman's estimator and its limitations.

those that are similar to the sample firms in all relevant characteristics. It is widely applied in very diverse fields of accounting study.

A common technique in the matched sample design is to compare sample firms with non-sample firms having similar ex ante characteristics, for instance size, profitability, industry, and growth. With a small number of characteristics, matching is straightforward. However, as characteristics increases, it is difficult to determine along which dimensions to match units or which weighting scheme to adopt (Dehejia and Wahba, 2002). Heckman, Ichimura, and Todd (1997) point out that in practise it is often difficult to match on high dimensional.[9] This problem is known as the “curse of dimensionality”. Conclusions may not be reliable if significant differences exist between the two set of firms after using traditional matching methods. I use propensity score-matching method to mitigate this problem, which I discuss further below.

4.2. Propensity score matching

Rosenbaum and Rubin (1983) suggest matching methods based on the propensity score. The propensity score is the probability that an agent takes treatment conditional on the available covariates. The point of using propensity score is that it substantially reduces the dimensionality of matching problem (Dehejia and Wahba, 2002). This single variable (estimated propensity score) can control for differences between treated and untreated comparison groups. Although propensity score can potentially correct for sample selection bias, it should be noted that it is no way guaranteed to solve the evaluation problem in every case. Matching procedures based on this probability are

[9] For example, Li and Zhao (2006) show that matching on multiple firm characteristics simultaneously is difficult.

known as propensity score matching (PSM). The method is relatively new in accounting literature but it is widely applied when evaluating labour market policies (see e.g., Heckman, Ichimura, and Todd, 1997).[10]

The basic idea in this study is to match treatment firms, that is, firms that report impairment write-offs, with control firms based on the probability of reporting impairment write-offs. The propensity score $p(x)$ is as follows,

$$p(X_i) \equiv pr(D_i = 1 | X_i) = E(D_i | X_i). \tag{5}$$

where D is the disclosure indicator: $D = 1$ for firms that report material impairment write-offs and $D = 0$ for non-reporting firms. X is the vector of covariates. The conditional probability is usually computed from a discrete choice model. Logit or probit models are preferred over the linear probability model (e.g., OLS regression), because the well-known shortcomings of the linear probability model (Caliendo and Kopeinig, 2008). I estimate one propensity score for the whole sample period.[11] However, to control for the possibility of omitted time-specific macro-economic effects, I match control firms on a year-by-year basis. Furthermore, year-by-year matching ensures that future returns are aligned in calendar time.

I choose conditioning variables x to include economic factors that are associated with impairment write-offs and subsequent stock returns. In a similar setting Li and Zhao (2006) point out that, if a variable affects only the write-off decisions but not

[10] For example, Vasvari (2006) uses PSM to control endogeneity of managerial incentives. Doyle, Ge, and McVay (2007) control for self-selection of material internal control weaknesses.

[11] I use local optimal ("greedy") algorithm to ensure that a match is always found for all impairment write-offs firms. The matching algorithm used in this study is developed by Parsons (2001). This algorithm makes "best" matches first and "next-best" matches next, while each control is selected at most once (see Parsons, 2001, for further details).

stock returns, it will not contaminate the evaluation of ex post stock returns. On the other hand, a variable may affect only stock returns but not write-off decisions. In this case selection bias does not occur because this variable will be identically distributed between write-off and non-write-off firms.

Earnings components (CF_t, $NACC_t$, and $DACC_t$) are included to control for firms' underlying earnings structure. Annual return (R_t) is a proxy for news. Since firm size could be a determinant of write-off decision and subsequent performance, I control for size by including the natural logarithm of market value of equity ($Size_t$). The market-to-book ratio (MTB_t) measures the extent to which book value understates equity value. The natural logarithm of lagged total assets ($LnAssets_{t-1}$) controls for firms' asset base. The ratio of property, plant, and equipment to total assets ($LTA\%_{t-1}$) proxies for the proportion of fixed assets and it is attempted to capture SFAS 144 impairment write-offs. The ratio of goodwill to total assets ($GW\%_{t-1}$) proxies for the proportion of intangible assets and it is attempted to capture SFAS 142 impairment write-offs. A dichotomous variable ($AnCov_t$) indicates whether the firm is followed by analysts and it proxies the degree of available information about a stock. A dichotomous variable ($Loss_t$) is coded one for firms where earnings before impairment write-offs is negative in an attempt to control for "big bath" incentive. Finally, I control for year and industry fixed effects. The propensity score in this study is the probability of the following logit model (firm subscripts omitted):

$$p(WO_t) = \alpha + \beta_1 CF_t + \beta_2 NACC_t + \beta_3 DACC_t + \beta_4 R_t + \beta_5 Size_t + \beta_6 MTB_t +$$

$$\beta_7 LnAssets_{t-1} + \beta_8 LTA\%_{t-1} + \beta_9 GW\%_{t-1} + \beta_{10} AnCov_t +$$

$$\beta_{11} Loss_t + fixed\ effects + \varepsilon_t \quad (6)$$

5. Results of propensity score matching

Table 7 presents the estimates of the propensity score model. Among the variables, the most significant predictive variables are $Size_t$, $LnAssets_{t-1}$, and $Loss_t$. As expected, $LTA\%_{t-1}$ and $GW\%_{t-1}$ are significant in predicting the likelihood of impairment write-offs. Excepted for industry fixed effects (not reported) all the other variables are insignificant in predicting impairment write-offs. Note that the main purpose of the propensity score estimation in not to maximize the probability of successful prediction into treatment but to balance all covariates.

Panel A of Table 8 presents matching quality of ex ante firm characteristics over the period from 2003 to 2005. I use three methods to check whether the matching procedure is able to balance the distribution of the relevant (observable) variables in both the control and treatment group. First, I use a two-sample *t*-test to check if there are significant differences in covariate for both groups. Second, I use the standardized bias (SB) as indicator of the match quality, as suggested by Rosenbaum and Rubin (1985). SB values below 5% are seen as sufficient (Caliendo and Kopeinig, 2008). Third, I re-estimate the propensity score on the matched sample and compare the pseudo R^2 before and after matching, as suggested by Sianesi (2004). After matching the pseudo R^2 should be fairly low if the matching is able to balance the distribution of the relevant variables in both samples. All methods confirm that there are not significant differences between the samples, indicating that propensity score matching was successful. As intended, the only difference between the samples is due to impairment write-offs (WO_t).

Panel B of Table 8 provides the difference in subsequent returns between impairment write-off and control firms during the period from 2003 to 2005. Differences between sample and control firms are evaluated using the *t*-test and the Wilcoxon signed rank test. Under earnings fixation hypothesis investors are surprised when accruals reverse in subsequent periods and abnormal returns reflect the corresponding price adjustment. However, the results show that there are no significant differences in mean or median future returns between *WO* and control sample firms. This is inconsistent with the earnings fixation hypothesis proposed by Sloan (1996).

The prior literature on special items has focused on material write-offs (e.g., Elliot and Shaw, 1988). As a robustness test, I include only material write-off firms in the sample and match these firms with non-write-off firms and find similar results.[12]

6. Conclusions

Sloan (1996) is the first to document the accruals anomaly, the negative relation between accruals and subsequent stock returns. In this paper I investigate the effects of the recent and prominent adoption of fair-value accounting on the market valuation of accruals using a sample of firm-years from 2003 to 2005. The results show that investors rationally price different earnings components when setting prices. Further analysis confirms that there are no significant differences in future returns between impairment write-off and control sample firms. These results are inconsistent with the

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[12] These results are available upon request.

earnings fixation hypothesis proposed by Sloan (1996). I interpret the result to suggest that concerns about fair-value accounting leading to significant security mispricing are not warranted.

It is common in accounting research that sample firms are fundamentally different from other firms. Although propensity score matching reduces bias it is not guaranteed to produce reliable estimates of market efficiency. However, since two different research designs produce similar results this adds confidence to the inferences of the study. In my view, propensity score matching offers several promising applications for future accounting research.

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Table 1 Sample selection criteria

	Total
Observations of CF_{t-1}, $Size_{t-1}$, $\Delta Sales_t$, E_t, CF_t, $Size_t$, MTB_t and R_t	13,035
1. Less financial institutions (SIC 6000–6999)	1,089
	11,946
2. Less: negative book value of equity	390
	11,556
3. Less: Positive total impairment values	23
	11,533
4. Less: R_{t+1} unavailable	3,059
	8,474
5. Less: The top and bottom one-half percent of E_t and R_t variables	158
	8,316
6. Less: Fewer than 15 observations in industry-year cross-section	626
Full sample	7,690

Notes:

E_t is net income (Worldscope #04001) in year *t*. CF_t is cash from operations (#04860) in year *t*. The above variables are deflated by lagged market value of equity (Datastream MV), measured three months after the fiscal year-end of year *t–1*. $Size_t$ is the natural logarithm of the market value of equity (in millions), measured three months after the fiscal year-end *t*. $\Delta Sales_t$ is the change in sales (#01001) from period *t–1* to *t*. MTB_t is the ratio of the market value of equity (Datastream MV) to the book value of equity (#03995), measured at the end of the fiscal year-end of year *t*. R_t is annual return from *t–1* to *t*, calculated for a 12-month period beginning 3 months after the end of the fiscal year *t–1*.

Table 2 Fama-MacBeth cross-sectional estimation of discretionary accruals

Intercept	$\Delta Sales_t$	PPE_t	CF_t	CF_{t-1}	Adj. R^2
0.014	0.043	–0.047	–0.611	0.166	67.17%
(3.31)	(3.92)	(–8.49)	(–20.86)	(4.97)	

Notes:

This table presents the average of 102 annual cross-sectional regression coefficients together with their *t*-statistics (in parentheses) of the following accrual model (firm subscripts omitted):

$$PreACC_t = \alpha_0 + \alpha_1 \Delta Sales_t + \alpha_2 PPE_t + \alpha_3 CF_t + \alpha_4 CF_{t-1} + \varepsilon_t$$

$PreACC_t$ is accruals before impairment write-offs in year *t*. Accruals is cash from operations (Worldscope #04860) minus net income (#04001). Impairment write-offs is the sum of the impairment of goodwill (#18225), impairment of other intangibles (#18226), and impairment of PPE (#18274). $\Delta Sales_t$ is the change in sales (#01001) from period *t–1* to *t*. PPE_t is gross property, plant, and equipment (#02301) in year *t*. CF_t is cash from operations (#04860) in year *t*. All variables are deflated by lagged market value of equity (Datastream MV), measured three months after the fiscal year-end of year *t-1*.

Table 3 Summary statistics for 7,690 firm-year observations for the period 2003–2005

Panel A: Descriptive statistics

Variable	Mean	Std	25%	Median	75%	Min	Max
E_t	–0.008	0.181	–0.027	0.041	0.069	–1.772	0.555
CF_t	0.074	0.205	0.010	0.072	0.136	–1.740	3.356
ACC_t	–0.082	0.202	–0.105	–0.041	–0.009	–4.095	1.575
$NACC_t$	–0.072	0.161	–0.095	–0.047	–0.017	–4.105	1.549
$DACC_t$	0.000	0.100	–0.023	0.009	0.035	–1.017	1.593
WO_t	–0.010	0.061	0.000	0.000	0.000	–1.824	0.000
$Size_t$	6.066	1.975	4.646	5.977	7.380	0.742	12.854
MTB_t	4.708	64.898	1.483	2.321	3.844	0.100	5595.1
R_t	0.405	0.880	–0.068	0.197	0.580	–0.727	7.083
SAR_t	0.000	0.801	–0.132	–0.106	0.207	–2.196	6.482
R_{t+1}	0.186	0.616	–0.132	0.088	0.344	–0.985	13.571
SAR_{t+1}	0.000	0.616	–0.314	–0.074	0.174	–1.532	13.340

Table 3 continued

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

Variable	E_t	CF_t	ACC_t	$NACC_t$	$DACC_t$	WO_t	$Size_t$	MTB_t	R_t	SAR_t	R_{t+1}	SAR_{t+1}
E_t		0.480	0.428	0.072	0.543	0.334	0.243	–0.025[c]	–0.080	0.023[c]	–0.003[a]	0.028[c]
CF_t	0.597		–0.606	–0.743	0.000	–0.047	0.124	–0.022[c]	0.051	0.062	0.117	0.123
ACC_t	0.155	–0.542		0.821	0.486	0.347	0.091	0.001[a]	–0.123	–0.042	–0.122	–0.100
$NACC_t$	–0.211	–0.695	0.655		0.000	0.080	0.035	0.008[a]	–0.164	–0.091	–0.117	–0.098
$DACC_t$	0.431	0.036	0.458	–0.186		–0.037	0.094	–0.006[a]	0.007[a]	0.033	–0.028[c]	–0.017[a]
WO_t	0.135	–0.060	0.227	0.097	0.041		0.057	–0.007[a]	0.014[a]	0.047	–0.047	–0.043
$Size_t$	0.272	0.235	0.019[a]	–0.070	0.096	–0.080		0.006[a]	–0.038	0.177	–0.115	–0.011[a]
MTB_t	–0.096	–0.242	0.241	0.227	0.029[c]	0.091	0.246		0.035	0.035	–0.015[a]	–0.014[a]
R_t	0.249	0.230	–0.108	–0.238	0.129	0.042	0.094	0.189		0.910	–0.082	–0.098
SAR_t	0.281	0.204	–0.015[a]	–0.118	0.104	0.028[c]	0.354	0.284	0.813		–0.144	–0.105
R_{t+1}	0.136	0.206	–0.103	–0.133	0.022[b]	–0.017[a]	0.023[c]	–0.150	–0.053	–0.089		0.984
SAR_{t+1}	0.156	0.208	–0.081	–0.112	0.026[c]	–0.026[c]	0.152	–0.105	–0.063	–0.016[a]	0.967	

Notes:

E_t is net income (#04001) in year *t*. CF_t is cash from operations (#04860) in year *t*. ACC_t is accruals in year *t*, which equals to $(E_t - CF_t)$. $NACC_t$ is nondiscretionary accruals in year *t* and it is the fitted value from the Eq. (1). $DACC_t$ is discretionary accruals in year *t* and it is the residual from the Eq. (1). WO_t is impairment write-offs in year *t*, which equals to impairment of goodwill (#18225) + impairment of other intangibles (#18226) + impairment of PPE (#18274). The above variables are deflated by lagged market value of equity (Datastream MV), measured three months after the fiscal year-end of year *t-1*. $Size_t$ is the natural logarithm of the market value of equity (in millions), measured three months after the fiscal year-end *t*. MTB_t is the ratio of the market value of equity (Datastream MV) to the book value of equity (#03995), measured at the end of the fiscal year-end. R_t is annual return from *t–1* to *t*, calculated for a 12-month period beginning 3 months after the end of the fiscal year *t–1*. SAR_t is size-adjusted return from *t–1* to *t*. All correlations are significant at $p < 0.01$, except as follows: [a] not significant, [b] significant at $p < 0.10$, and [c] significant at $p < 0.05$.

Table 4 Results from ordinary least squares regressions of future size-adjusted returns on cash flows and accruals for 7,690 firm-year observations for the period 2003–2005

	OLS	Mishkin			
Variable	Pooled Coefficients	Pooled Forecasting Coefficients	Pooled Pricing Coefficients	Difference between Coefficients	$\gamma\ OLS = \beta(\gamma_j - \gamma_j^*)$
Intercept	–0.031	0.000	0.045	–0.044	–0.031
	(–4.21)	(0.16)	(4.22)	(16.63)	
CF_t	0.291	0.815	0.411	0.405	0.286
	(6.93)	(60.40)	(6.67)	(41.29)	
ACC_t	–0.121	0.614	0.788	–0.174	–0.123
	(–2.83)	(44.66)	(13.16)	(8.00)	
β (Mishkin)		0.707			
N	7,690	7,618			
Adj. R^2 (OLS)	1.59%				
Convergence criteria (Mishkin)		11			

Notes:

This table reports results from the following OLS regression (firm subscripts omitted):

$$SAR_{t+1} = \phi_0 + \phi_1 CF_t + \phi_2 ACC_t + u_{t+1},$$

and the nonlinear maximum likelihood estimation of the following equations:

Forecasting equation: $E_{t+1} = \gamma_0 + \gamma_1 CF_t + \gamma_2 ACC_t + v_{t+1}$

Pricing equation: $SAR_{t+1} = \beta(E_{t+1} - \gamma_0^* - \gamma_1^* CF_t - \gamma_2^* ACC_t) + \varepsilon_{t+1}$.

See table 3 for variable definitions. Values in parentheses are *t*-statistics.

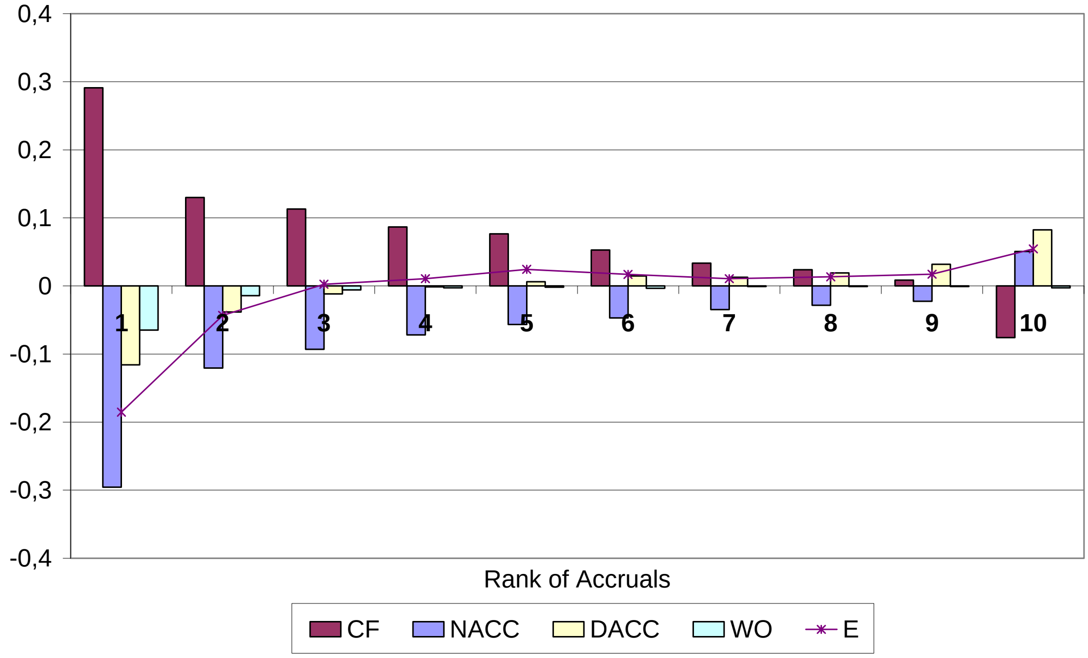

Fig. 1 The average level of CF_t, $NACC_t$, $DACC_t$, WO_t, and E_t across accrual deciles. The sample consist 7,690 firm-years from 2003–2005. Firm-year observations are ranked annually and assigned in ascending order to decile portfolios based on accruals. Decile 1 consists of firms with the most negative accruals. Decile 10 consists of firms with the most positive accruals. E_t is net income (#04001) in year *t*. CF_t is cash from operations (#04860) in year *t*. $NACC_t$ is nondiscretionary accruals in year *t* and it is the fitted value from the Eq. (1). $DACC_t$ is discretionary accruals in year *t* and it is the residual from the Eq. (1). WO_t is impairment write-offs in year *t*, which equals to impairment of goodwill (#18225) + impairment of other intangibles (#18226) + impairment of PPE (#18274). All variables are deflated by lagged market value of equity (Datastream MV), measured three months after the fiscal year-end of year *t-1*

Table 5 Selected variables for portfolios sorted by accruals for 7,690 firm-years for the period 2003–2005

	Lowest	2	3	4	5	6	7	8	9	Highest
Panel A: Earnings components										
E_t^a	–0.185	–0.043	0.002	0.011	0.024	0.017	0.011	0.013	0.017	0.054
CF_t^a	0.291	0.130	0.113	0.087	0.077	0.053	0.033	0.024	0.008	–0.076
$NACC_t^a$	–0.296	–0.121	–0.093	–0.072	–0.057	–0.047	–0.035	–0.029	–0.022	0.051
$DACC_t^a$	–0.116	–0.038	–0.012	–0.001	0.006	0.015	0.013	0.019	0.032	0.082
WO_t^a	–0.065	–0.014	–0.006	–0.003	–0.002	–0.003	–0.001	–0.001	–0.001	–0.003

Panel B: Firm characteristics										
$Size_t$ [b]	5.162	5.669	6.205	6.389	6.563	6.534	6.442	6.194	5.553	5.291
MTB_t [b]	1.408	1.786	2.034	2.108	2.484	2.952	3.130	3.379	2.907	1.988
$SalesGr_t$ [b]	0.052	0.077	0.093	0.097	0.106	0.116	0.125	0.137	0.144	0.177
Loss (%)	58.5	43.6	31.6	27.4	21.7	21.7	26.6	26.1	26.4	20.3
Coverage (%)	61.7	68.9	76.0	80.4	83.6	82.8	82.5	79.2	73.6	60.2
R_t [a]	0.588	0.487	0.457	0.387	0.331	0.316	0.246	0.266	0.339	0.634
SAR_t [a]	0.076	0.030	0.044	0.000	–0.019	–0.032	–0.098	–0.084	–0.056	0.140
R_{t+1} [a]	0.345	0.221	0.211	0.189	0.152	0.145	0.144	0.127	0.169	0.154
SAR_{t+1} [a]	0.126	0.023	0.021	0.012	–0.017	–0.023	–0.027	–0.042	–0.012	–0.060

Notes:

See table 3 for variable definitions. [a] denote mean, [b] denote median. See table 3 for variable definitions. Portfolios are formed annually by assigning firms into deciles based on the magnitude of accruals (ACC_t) in year *t*.

Table 6 Future size-adjusted returns on earnings components

Variable	Predicted sign	One-year-ahead size-adjusted return
Intercept		–0.024
		(–0.80)
CF_t	+	0.262
		(2.65)
$NACC_t$	–	–0.096
		(–0.31)
$DACC_t$	–	–0.120
		(–1.06)
WO_t	–	–0.372
		(–0.97)
Industry controls		Included
N		7,690
R^2		2.31%

Notes:

This table reports results from the following OLS regression (firm subscripts omitted):

$$SAR_{t+1} = \phi_0 + \phi_1 CF_t + \phi_2 NACC_t + \phi_3 DACC_t + \phi_4 WO_t + \textit{fixed effects} + u_{t+1}$$

Variables are as defined in table 3. To save space, parameter estimates for the fixed year and industry effects are not reported. Industry classifications are based to Barth et al. (1998). The sample period is 2003–2005. Values in parentheses are *t*-statistics clustered by year. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels (two-tailed).

Table 7 Estimates of the propensity score model for the period 2003–2005

Variable	Predicted sign	$p(WO_t)$
Intercept		–10.781 (0.000) [a]
CF_t	+	–0.138 (0.609)
$NACC_t$	+	–0.245 (0.442)
$DACC_t$	+	0.312 (0.326)
R_t	–	–0.007 (0.877)
$Size_t$	–	–0.332 (0.000)
MTB_t	?	0.002 (0.449)
$LnAssets_{t-1}$	+	0.550 (0.000)
$LTA\%_{t-1}$	+	0.259 (0.005)
$GW\%_{t-1}$	+	0.540 (0.005)
$AnCov_t$	?	0.067 (0.469)
$Loss_t$	+	0.675 (0.000)
Year controls		Included
Industry controls		Included
N where $WO > 0$		1,493
N		7,690
McFadden pseudo R^2		7.0%

Notes:

Parameter estimates are based on the following logit model (firm subscripts omitted):

$$p(WO_t) = \alpha + \beta_1 CF_t + \beta_2 NACC_t + \beta_3 DACC_t + \beta_4 R_t + \beta_5 Size_t + \beta_6 MTB_t + \beta_7 LnAssets_{t-1} + \beta_8 LTA\%_{t-1} + \beta_9 GW\%_{t-1} + \beta_{10} AnCov_t + \beta_{11} Loss_t + fixed\ effects + \varepsilon_t$$

Variables are as defined in table 3 except: $LnAssets_{t-1}$ is the logarithm of total assets (#02999) in year *t–1*. $LTA\%_{t-1}$ is the ratio of property, plant, and equipment (#02301) to total assets in year *t–1*. $GW\%_{t-1}$ is the ratio of goodwill (#18280) to total assets in year *t–1*. $AnCov_t$ is a dummy variable coded as 1 if there is an analyst earnings forecasting during the third month after the fiscal year end of year *t* in IBES and 0 otherwise. $Loss_t$ is a dummy variable coded as 1 if earnings before impairment write-offs is negative and 0 otherwise in year *t*. To save space, parameter estimates for the fixed year and industry effects are not reported. Industry classifications are based to Barth et al. (1998). [a] *p*-values given in parentheses.

Table 8 Tests of propensity score matching

Panel A: Assessing the matching quality

	E_t	CF_t	$NACC_t$	$DACC_t$	WO_t	R_t	$Size_t$	MTB_t
Mean tests (paired *t*-tests)	0.051***	0.001	0.000	0.000	0.050***	–0.001	–0.066	–3.829
Standardized bias	–24.25%	–0.60%	0.19%	–0.10%	–53.99%	0.15%	3.23%	3.69%
Pseudo R^2 before matching	7.0%							
Pseudo R^2 after matching	0.5%							

Panel B: Subsequent returns for WO and control sample

Year	N	Mean R_{t+1} WO firms	Mean R_{t+1} control firms	Median R_{t+1} WO firms	Median R_{t+1} control firms
2003	507	0.317	0.258	0.178	0.154
2004	483	0.137*	0.196	0.069	0.097
2005	496	0.148	0.160	0.081	0.098
Overall	1,486	0.202	0.205	0.101	0.113

Notes:

See table 3 for variable definitions. The standardized bias (SB) is defined as the difference of the sample means as a percentage of the square root of average of sample variances in both groups. $SB = 100 * (\overline{X}_1 - \overline{X}_0) / \left\{\sqrt{(V_1(X) + V_0(X))/2}\right\}$. $\overline{X_1}$ $(\overline{V}_1)$ is the mean (variance) for impairment write-off group and $\overline{X_0}$ $(\overline{V}_0)$ the analogue for the control group. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels for two-tailed *t*-tests of differences in means. ###,##, and # indicate statistical significance at the 1%, 5%, and 10% levels for two-tailed Wilcoxon tests of differences in medians.