The Econometrics of Estimating Unexpected Accruals*

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Abstract

This study takes on the theory of unexpected accruals originally developed by Jones (1991), but incorporates the points made by Kang and Sivaramakrishnan (1995). We identify further additional econometric deficiencies in the research design that underlie the analytical formulation of Jones (1991) as well as the modification offered by Kang and Sivaramakrishnan (1995). Specifically, we recognise two types of errors in measurement of expected accruals; the one is due to the fact that the variables used to proxy expected accruals contain certain portion of unexpected accruals and the second is due to omitted variables internal to accounting. In addition, we identify the precise form of simultaneity bias that is introduced by the inclusion of endogenous variables in both sides of the expectation equation. We also analyse the effect of omitted variables that are external to accounting and how these can be controlled using panel data mehods. We show that most empirical applications that attempt to estimate unexpected accruals are ad hoc in nature and ignore important features of the data that may compromise the validity of their results.

Key Words: Earnings Management, Earnings Properties, Unexpected Accruals, Financial Analysis, Dynamic Panel Data.

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1 Introduction

One of the most celebrated accounting research articles to date is Jones' (1991) study on Earnings Management during Import Relief Investigations.[1] This seminal work focuses on the aggregate accrual transactions (including deferrals) of those firms that may benefit from import relief and therefore have incentives to manage earnings downwards in order to receive or maximise the relief. Jones (1991) develops an expectation model that presumably decomposes total accruals into those that are naturally expected and could be predicted, and those that are abnormal and suspect to serve purposes other than the normal operations of the business. The focus on accruals is based on the assertion that cash flow transactions are more transparent and cannot be used in a consistent manner for directing earnings towards a threshold. Jones (1991) results suggest that firms indeed exercise discretion over reported earnings through manipulation of accruals during import relief investigations.[2]

The original Jones (1991) model and a modified version proposed by Dechow, Sloan and Sweeney (1995) have been applied to a variety of contexts and international settings, and still continue to enjoy widespread recognition as the most appropriate tools for measuring the unexpected part of accruals.[3] However, the approach has also met its critics. Holthausen, Larcker and Sloan (1995, p.66) describe the model as "poorly specified", where Bernard and Skinner (1996, p.324) ask for "methodologically more reliable ways of measuring earnings management". Kang and Sivaramakrishnan (1995) are more specific and identify certain sources of misspecification. Like this study, they are also concerned with analytical correctness of the research methods employed and show that the original model suffers from simultaneity bias, errors in measurement and omitted variables.

This study takes on the theory of unexpected accruals originally developed by Jones (1991), but incorporates the points made by Kang and Sivaramakrishnan (1995). We identify further additional econometric deficiencies in the research design that underlie the analytical formulation of Jones (1991) as well as the modification offered by Kang and Sivaramakrishnan (1995). Specifically, we recognise two types of errors in measurement of expected accruals; the one is

[1] According to GoogleTM Scholar (http://scholar.google.com) and Harzing's Publish of Perish (www.harzing.com/index.htm, Tarma Software Research Pty Ltd), the research article by Jones (1991) has been cited more than 750 times to date, averaging to about 45 citations per year in journals, books, manuscripts and other published sources.

[2] This study is not concerned with uncovering the precise managerial incentives for manipulating earnings. For a review of the earnings management hypothesis see Burgstahler and Dichev (1997), Healy and Walhen (1998), Degeorge, Patel, and Zeckhauser (1999), Dechow and Skinner (2000), McNichols (2000), Skinner and Sloan (2002), Bhattacharya, Daouk and Welker (2002).

[3] The research design proposed by Jones (1991) has been applied in the investigation of avoidance of alternative minimum tax (Boynton, Dobbins and Plesko 1992), stimulating non-routine executive payments (Pourciau 1993), escaping debt covenant violations (DeFond and Jiambalvo 1994), increasing earnings before IPOs' (Perry and Williams 1994), maximizing bonus-based compensation (Holthausen, Larcker and Sloan 1995), smoothing of net income (Gaver, Gaver and Austin 1995), pricing of accruals (Subramanyam 1996; Sloan 1996), masking violations of GAAP (Beneish 1997), using voluntary disclosure of accruals to manage earnings (Kasnik 1999), measuring the mispricing of accruals (Xie 2001), examining the relationship between audit committees, board of directors and earnings management (Klein 2002), using private information and exercising of executive stock options (Bartov and Mohanran 2004), examining the role of specific accruals in various earnings management targets (Marquardt and Wiedman 2004), measuring performance-matched unexpected accruals (Kothari, Leone, and Wasley 2004), associating equity incentives to earnings management (Cheng and Warfield 2005), insider trading during IPOs' (Darrough and Rangan 2005), minimising superfund clean-up and transaction costs (Johnston and Rock 2005).

due to the fact that the variables used to proxy expected accruals contain certain portion of unexpected accruals and the second is due to omitted variables internal to accounting. In addition, we identify the precise form of simultaneity bias that is introduced by the inclusion of endogenous variables in both sides of the expectation equation. We also analyse the effect of omitted variables that are external to accounting and how these can be controlled using panel data mehods. We show that most empirical applications that attempt to estimate unexpected accruals are ad hoc in nature and ignore important features of the data that may compromise the validity of their results.

The study covers four types of data structures and explains the limitations and caveats for the methods applied in each of time series, cross sectional and pooled methods of analysis. To circumvent these problems we follow a panel data approach that enables us to control for firm-specific and industry specific unobserved time-invariant effects, as well as common time-specific effects that influence all firms in the sample or only firms in a given industry. In addition, our model allows for firm-specific heterogeneity in the slope coefficients of the variables, which is modelled as a function of the size of the firm. There is evidence in the literature that shows how size is instrumental in defining the level and sign of accruals (and deferrals). We show that our approach results in significant improvements in the estimates of the model parameters.[4]

The remaining of this paper proceeds as follows. The following section describes the development of the Jones (1991) model and the modifications made by Kang and Sivaramakrishnan (1995). It also discusses the various sources of bias that may arise in estimating both of these models when OLS is used or when unobserved heterogeneity is not taken intou account. Section 3 analyses the model we develop and estimate using panel data and the generalised method of moments. Section 4 describes the data and the final section reports the results from our empirical application.

2 The Unexpected Total Accruals Model and Econometric Biases

Jones (1991) builds upon the theory that purposeful intervention within earnings can be achieved to its greatest part through the management of accrual items. Conceptually, total accruals can be partitioned into those that arise due to usual business practices (expected part) and those whose direction and magnitude is managed so that earnings will meet certain targets (unexpected part). In this respect, the earnings identity can be rewritten to reflect the decomposition, so that:

$$Earnings \equiv Cash\ Flows + \ (Expected\ Accruals + Unexpected\ Accruals)\,.$$

For every firm $i = 1, 2, \ldots, I$ and firm-specific year $t = 1, 2, \ldots, T_i$, total accruals (TA) can be calculated using the following flow approach:

$$TA_{it} \equiv (\Delta CA_{it} - \Delta CASH_{it}) - (\Delta CL_{it} - \Delta STD_{it}) - DEP_{it} \quad (1)$$

where Δ is the first-difference time operator that transforms balance sheet stocks into flows for total current assets, CA, total cash and equivalent, $CASH$, total current liabilities, CL, and

[4] Given the added complexity of the proposed methodology, we will make available the Stata^{TM} routine upon request for applying this framework.

total short-term debt, STD. Depreciation, DEP, is already a flow that is taken directly from the income statement.[5] TA is then employed by Jones (1991) as a response variable in an ordinary least squares (OLS) regression on the change in sales revenue (ΔREV) and the level of gross level of property, plant and equipment (PPE), as follows:

$$\frac{TA_{it}}{A_{it-1}} = \alpha_0 + b_1 \frac{\Delta REV_{it}}{A_{it-1}} + b_2 \frac{PPE_{it}}{A_{it-1}} + e_{it} \tag{2}$$

where it is customary to deflate all variables with total assets of the previous period, A_{it-1}. The deflated change in revenues is then supposed to capture the variation of expected working capital accruals that is generated from revenue recognition, and the deflated PPE the variation of expected long-term accruals that is attributed to multiple operating cycles, such as depreciation and amortisation.[6] Subsequently, the fitted part of equation (2) is perceived as the part of accruals that is expected due to the normal operations of the firm $ETA_{it} = \widehat{\alpha}_0 + \widehat{b}_1 \frac{\Delta REV_{it}}{A_{it-1}} + \widehat{b}_2 \frac{PPE_{it}}{A_{it-1}}$, where $\widehat{(.)}$ indicates the OLS estimate of a parameter. The remaining variation of total accruals in the same regression is due to the error term, $\widehat{e}_{it}$, and this is assumed to capture unexpected accruals, UTA. In short, equation (2) expresses an expectation function for the endogenous variable TA_{it} and assumes strict exogeneity in the change of sales revenue, $REV_{it} - REV_{it-1}$, and the level of property, plant and equipment, PPE_{it} – namely, $covariance\left(\frac{\Delta REV_{it}}{A_{it-1}}, e_{it}\right) = covariance\left(\frac{PPE_{it}}{A_{it-1}}, e_{it}\right) = 0$. In this way ETA_{it} is orthogonal to UTA_{it}, which is a necessary condition in order to identify equation (2) using OLS.

2.1 Errors in Measurement for Expected Accruals

The use of the deflated ΔREV and PPE to capture expected accruals faces two measurement problems. First, these variables are also likely to be subject to managerial discretion and therefore they may contain a significant portion of unexpectedly abnormal accruals (Dechow et

[5] The calculation of TA under the flow approach of equation (1) is the most popular in the literature. Another way for calculating the flow of TA is to use the accounting identity *Accruals* $\equiv$ *Earnings* $-$ *Operating Cash Flows*, where flow information is now extracted directly from the cash flow statement and the income statement of the accounting period. Hribar and Collins (2002) compare the two flow approaches and conclude that the balance sheet calculation of equation (1) may introduce errors in accrual estimation especially following restructuring periods or business combinations. For this study, however, we insist on the flow approach of equation (1) because we want to evaluate the Jones model in specific. Also, while many studies have excluded tax refunds and tax payables from the caclulation of total accruals, the original Jones (1991) model includes tax-related items and Kang (1999) shows that their inclusion significantly improves the power of the model.

[6] There are several extensions of equation (2) in the literature. For instance, if revenues are expected to contain a significant component of receivables which are less likely to be managed then we may as well exclude them from revenue (Dechow, Sloan and Sweeney 1995; Holthausen, Larcker and Sloan 1995; Bernard and Skinner 1996). Moreover, in established capital markets managerial intervenence is less likely to occur through depreciation or amortisation expenses and therefore a restricted model that concentrates only on working capital accruals (i.e., $b_2 = 0$) may be more appropriate (Teoh, Welch and Wong 1998; DeFond and Jiambalvo 1994). Also, cash flows may be instrumental in defining the level and direction of accruals given the complementarity of the two accounts and the substantial variation of cash flows between firms (Guay, Kothari and Watts 1996; Shivakumar 1996; Dechow, Kothari and Watts 1998; Jeter and Shivakumar 1999; Garza-Gómez, Okumura and Kunimura 1999). It is also shown that the explanatory power may significantly increase by reformulating the model to fit expectations on the precise type of earnings management, such as the management of non-bad debts (Young 1999; Peasnell, Pope and Young 2000). For a more thorough review and comparison of unexpected accruals models that are derived from equation (2) see Healy and Wahlen (1999), Hansen (1999), Young (1999), Thomas and Zhang (2000) and Kothari, Leone and Wasley (2004).

al. 1995; Kang and Sivaramakrishnan 1995; Beneish 1997; Nelson, Elliot and Tarpley 2002). In this case ΔREV and PPE may no longer be ideal proxies for the specific research design and as a result, running OLS in equation (2) will yield biased estimates of the model parameters, even in large samples.[7] We can illustrate this point by noting that if in practice the proxy of expected accruals contains unexpected accruals too, it can be expressed as a weighted average between the true expected accruals, ETA^{true}, and UTA:

$$ETA = \gamma ETA^{true} + (1 - \gamma)\, UTA \tag{3}$$

where $0 \leq \gamma \leq 1$. Clearly, unless $\gamma = 1$ ΔREV and PPE will also contain certain portion of unexpected accruals. However, this implies that the explanatory variables are not orthogonal to the error term in the Jones model because:

$$\begin{aligned} & covariance\left(\alpha_0 + b_1 \frac{\Delta REV_{it}}{A_{it-1}} + b_2 \frac{PPE_{it}}{A_{it-1}}, e_{it}\right) = \\ = \; & covariance\left[\gamma ETA^{true} + (1-\gamma)\, UTA, UTA\right] = (1-\gamma)\, var\,(UTA) \neq 0 \end{aligned} \tag{4}$$

Therefore, the model cannot be identified using OLS.

The second problem in the Jones model is the existence of possible omitted variables internal to accounting system, which may exacerbate the above effect. For instance, equation (2) assumes that ΔREV and PPE are "sufficient" to capture the variation of expected accruals. However, we know that accounting bookkeeping demands a double entry recording for every transaction. This means that every sales transaction affects two accounts, one in the income statement (credit in sales revenue) and one in the balance sheet (debit in either cash or accounts receivables). It is very difficult to identify which accounts are to be included in a single regression such as equation (2). Indeed, Christodoulou and McLeay (2008) take on this predicament and show how a reconciliation of financial statements (i.e., balance sheet stocks observed at time t and $t-1$, and accrual and cash flows taken from time t) creates a vast network of accounting identities for a given accounting period and therefore the choice of explanatory variables in regression models with accounting data is not trivial.

All the above implies that ΔREV and PPE may not be accurate measures of ETA and any discrepancy between these variables will reflect an error in measuring ETA, denoted by m_{it}. Therefore, while the true model is given by $TA_{it} = ETA_{it} + UTA_{it} = \left(\alpha_0 + b_1 \frac{\Delta REV_{it}}{A_{it-1}} + b_2 \frac{PPE_{it}}{A_{it-1}} + m_{it}\right) + UTA_{it}$, in practice what we estimate equals:

$$TA_{it} = \alpha_0 + b_1 \frac{\Delta REV_{it}}{A_{it-1}} + b_2 \frac{PPE_{it}}{A_{it-1}} + e_{it}, \;\; e_{it} = m_{it} + UTA_{it} \tag{5}$$

Taking the simplest possible case where the measurement error in ETA is serially and contemporaneously uncorrelated with mean zero and variance equal to σ_m^2, it is easy to see that the covariance between the proxy of ETA and e_{it} is different from zero. In particular, we have:

$$covariance\left(\alpha_0 + b_1 \frac{\Delta REV_{it}}{A_{it-1}} + b_2 \frac{PPE_{it}}{A_{it-1}}, e_{it}\right) = covariance\,(ETA - m_{it}, m_{it} + UTA_{it}) = \sigma_m^2. \tag{6}$$

[7] Jones (1991, p.212) admitts this potential source of bias and explains that this type of error in measurement discussed above may well cause the explanatory variables to be endogeneous to the error term of equation (2) when "reported revenues may be affected to some extent by managers' attempts to decrease reported earnings". Yet, Jones fails to recognise that the accounting identity of earnings indicates that endogeneity is in fact inherent and unconditional to equation (2), i.e. the source of simultaneity bias that is explained below.

Hence, again the orthogonality condition between the explanatory variables and the error term is violated and the model cannot be identified using OLS.

2.2 Simultaneity Bias

Another major problem with estimating equation (2) using OLS is the fact that double-entry bookkeeping maintains that the explanatory variables in the Jones model will not be exogenous even if there are no errors in measurement for expected accruals. Essentially, this is because all three variables, TA, ΔREV and PPE, are determined simultaneously and therefore there is no such a unidirectional cause-and-effect relationship between the explanatory variables in equation (2) and TA.[8] To see this, suppress the deflator and the second explanatory variable in equation (2) and rewrite it as $(NI_{it} - CFO_{it}) = \alpha_0 + b_1 \Delta (NI_{it} - COSTS_{it}) + e_{it}$, where NI is net income, CFO is cash flow from operations and $COSTS$ are operating costs and expenses so that $REV \equiv (NI - COSTS)$. Therefore, it is evident that the existence of NI in both sides of the regression makes ΔREV endogenous and therefore the orthogonality condition between ΔREV and e breaks down. As a result, the OLS estimated parameters in (2) will be biased regardless of the sample size. To quantify this bias it is useful to augment (2) with the following two equations:

$$\frac{\Delta REV_{it}}{A_{it-1}} = \alpha_1 + c_1 \frac{TA_{it}}{A_{it-1}} + c_2 \frac{PPE_{it}}{A_{it-1}} + \varepsilon_{it} \tag{7}$$

and

$$\frac{PPE_{it}}{A_{it-1}} = \alpha_2 + d_1 \frac{TA_{it}}{A_{it-1}} + d_2 \frac{\Delta REV_{it}}{A_{it-1}} + v_{it}, \tag{8}$$

The system of three equations given by equations (2), (7) and (8) merely characterises the reconciliation feature of financial statements. Substituting (2) into (7) and (8) we obtain respectively:

$$\begin{aligned}
\frac{\Delta REV_{it}}{A_{it-1}} &= \alpha_1 + c_1 \left[\alpha_0 + b_1 \frac{\Delta REV_{it}}{A_{it-1}} + b_2 \frac{PPE_{it}}{A_{it-1}} + e_{it} \right] + c_2 \frac{PPE_{it}}{A_{it-1}} + \varepsilon_{it} \\
&= \alpha_1 + c_1 \alpha_0 + c_1 b_1 \frac{\Delta REV_{it}}{A_{it-1}} + (c_1 b_2 + c_2) \frac{PPE_{it}}{A_{it-1}} + c_1 e_{it} + \varepsilon_{it} \\
&= \frac{\alpha_1 + c_1 \alpha_0}{1 - c_1 b_1} + \frac{c_1 b_2 + c_2}{1 - c_1 b_1} \frac{PPE_{it}}{A_{it-1}} + \frac{c_1}{1 - c_1 b_1} e_{it} + \frac{1}{1 - c_1 b_1} \varepsilon_{it} \\
&= \alpha_1^* + c_2^* \frac{PPE_{it}}{A_{it-1}} + \varepsilon_{it}^*
\end{aligned} \tag{9}$$

[8] Christodoulou and McLeay (2008) show how the double-entry bookkeeping model reports numbers that are part of a vast network of endogenous relationships. Within this network (or matrix), they are able to describe total accruals as an equilibrium node for many contemporaneous information flows within the firm. Specifically, they show that the decisions which shape accruals are jointly determined by financing, investment and operating functions, involving balance sheet stocks, cash flows and accrual flows. Under double entry, this gives rise to two accounting identities of the same magnitude but of different sign. They also discuss the biases arising from a single regression that uses accounting in both sides of the equation and propose instead an approach based on structural systems of equations.

and

$$\begin{aligned}
\frac{PPE_{it}}{A_{it-1}} &= \alpha_2 + d_1\left[\alpha_0 + b_1\frac{\Delta REV_{it}}{A_{it-1}} + b_2\frac{PPE_{it}}{A_{it-1}} + e_{it}\right] + d_2\frac{\Delta REV_{it}}{A_{it-1}} + v_{it} \\
&= \alpha_2 + d_1\alpha_0 + (d_1b_1 + d_2)\frac{\Delta REV_{it}}{A_{it-1}} + d_1b_2\frac{PPE_{it}}{A_{it-1}} + d_1e_{it} + v_{it} \\
&= \frac{\alpha_2 + d_1\alpha_0}{1-d_1b_2} + \frac{d_1b_2 + d_2}{1-d_1b_2}\frac{\Delta REV_{it}}{A_{it-1}} + \frac{d_1}{1-d_1b_2}e_{it} + \frac{1}{1-d_1b_2}v_{it} \\
&= \alpha_2^* + b_2^*\frac{\Delta REV_{it}}{A_{it-1}} + v_{it}^* \qquad (10)
\end{aligned}$$

where $\alpha_1^* = \frac{\alpha_1+c_1\alpha_0}{1-c_1b_1}$, $c_2^* = \frac{c_1b_2}{1-c_1b_1}$, $\alpha_2^* = \frac{\alpha_2+d_1\alpha_0}{1-d_1b_2}$, $b_2^* = \frac{d_1b_2+d_2}{1-d_1b_2}$, $\varepsilon_{it}^* = \frac{c_1}{1-c_1b_1}e_{it} + \frac{1}{1-c_1b_1}\varepsilon_{it}$ and $v_{it}^* = \frac{d_1}{1-d_1b_2}e_{it} + \frac{1}{1-d_1b_2}v_{it}$.

Furthermore, substituting (10) into (9) yields:

$$\begin{aligned}
\frac{\Delta REV_{it}}{A_{it-1}} &= \alpha_1^* + c_2^*\left[\alpha_2^* + b_2^*\frac{\Delta REV_{it}}{A_{it-1}} + v_{it}^*\right] + \varepsilon_{it}^* \\
\frac{\Delta REV_{it}}{A_{it-1}} &= \widetilde{\alpha}_1 + \widetilde{\varepsilon}_{it} \qquad (11)
\end{aligned}$$

where $\widetilde{\alpha}_1 = \frac{\alpha_1^*+c_2^*\alpha_2^*}{1-c_2^*b_2^*}$ and $\widetilde{\varepsilon}_{it} = \frac{c_2^*}{1-c_2^*b_2^*}v_{it}^* + \frac{1}{1-c_2^*b_2^*}\varepsilon_{it}^*$.

Thus, it is obvious that the covariance between $\frac{\Delta REV_{it}}{A_{it-1}}$ and e_{it} in (2) equals:

$$\begin{aligned}
cov\left(\frac{\Delta REV_{it}}{A_{it-1}}, e_{it}\right) &= cov\left[\left(\widetilde{\alpha}_1 + \widetilde{\varepsilon}_{it}\right)e_{it}\right] = cov\left[\left(\frac{c_2^*}{1-c_2^*b_2^*}v_{it}^* + \frac{1}{1-c_2^*b_2^*}\varepsilon_{it}^*\right)e_{it}\right] \\
&= cov\left[\left(\frac{d_1}{1-d_1b_2}e_{it} + \frac{c_1}{1-c_1b_1}e_{it}\right)e_{it}\right] = b\sigma_e^2 \qquad (12)
\end{aligned}$$

where $b = \frac{d_1+c_1-c_1d_1(b_1+b_2)}{1-d_1b_2-c_1b_1+b_1c_1d_1b_2}$ and $\sigma_e^2 = var\left(e_{it}\right)$. This implies that the OLS estimate of b_1 in (2) (and similarly that of b_2) is going to be biased and inconsistent. Specifically, it is straightforward to show that in this case the asymptotic bias of $\widehat{b}_1$ equals:

$$\begin{aligned}
& \text{plim}_{IT\to\infty}\left(\widehat{b}_1 - b_1\right) \\
= \; & \frac{cov\left(\frac{\Delta REV_{it}}{A_{it-1}}, e_{it}\right)\cdot var\left(\frac{PPE_{it}}{A_{it-1}}\right) - cov\left(\frac{PPE_{it}}{A_{it-1}}, e_{it}\right)\cdot cov\left(\frac{\Delta REV_{it}}{A_{it-1}}, \frac{PPE_{it}}{A_{it-1}}\right)}{var\left(\frac{PPE_{it}}{A_{it-1}}\right)\cdot var\left(\frac{\Delta REV_{it}}{A_{it-1}}\right) - \left[cov\left(\frac{\Delta REV_{it}}{A_{it-1}}, \frac{PPE_{it}}{A_{it-1}}\right)\right]^2} \\
= \; & \frac{b\sigma_e^2\cdot\sigma_{PPE}^2 - \delta\sigma_\varepsilon^2\cdot b_2^*\sigma_{\Delta REV,PPE}}{\sigma_{PPE}^2\cdot\sigma_{REV}^2 - \left[\sigma_{\Delta REV,PPE}\right]^2} \qquad (13)
\end{aligned}$$

where σ_{PPE}^2 and σ_{REV}^2 denote the variance of $\frac{PPE_{it}}{A_{it-1}}$ and $\frac{\Delta REV_{it}}{A_{it-1}}$ respectively and $\sigma_{\Delta REV,PPE} = cov\left(\frac{\Delta REV_{it}}{A_{it-1}}, \frac{PPE_{it}}{A_{it-1}}\right)$. Therefore, this bias will only be zero if $\sigma_e^2 = 0$, i.e. if there is no UTA in the model.

When $T = 1$ or $I = 1$ the pooled model in (2) reduces to a cross-sectional or a time series model respectively. In this case there is no change in the final expression provided in (13) – the only difference is that the plims are taken over I and T respectively. Therefore, the same problem persists even when one runs a single cross section or a single time series regression alone.

To aleviate the errors in measurement and simultaneity problems Kang and Sivaramakrishnan (1995) first modify equation (1) and calculate total accruals using balance sheet stocks as follows:

$$TA'_{it} \equiv (CA_{it} - CASH_{it}) - (CL_{it} - STD_{it}) - DEP_{it} \qquad (14)$$

The exception is the income statement flow of depreciation expense DEP. Given the balance sheet based calculation of TA'_{it}, Kang and Sivaramakrishnan (1995) then develop the following model that captures the expected variation of accrual balances:

$$\frac{TA'_{it}}{A_{it-1}} = \alpha'_0 + b'_1 \frac{REV_{it}\left(\frac{AR_{it-1}}{REV_{it-1}}\right)}{A_{it-1}} + b'_2 \frac{PPE_{it}\left(\frac{DEP_{it-1}}{PPE_{it-1}}\right)}{A_{it-1}} + b'_3 \frac{EXP_{it}\left(\frac{NCA_{it-1}-AR_{it-1}}{EXP_{it-1}}\right)}{A_{it-1}} + e'_{it} \tag{15}$$

where AR is accounts receivables, EXP is operating expenses comprising of cost of goods sold plus selling and administrative expenses before depreciation, and $NCA = (CA - CASH) - (CL - STD)$ is net current assets. The main conceptual difference between the two approaches is that equation (15) attempts the decomposition of accruals into expected and unexpected using year-end balances, whereas equation (2) uses accrual flows. Also, notice that the explanatory variables of equation (15) represent products of turnover ratios and current account levels that combine both stocks and flows.[9] More importantly, it includes the additional covariate of EXP that is intended to capture the expected accruals related to the recognition of operating expenses. This seems a more plausible specification than equation (2) which assumes that normal level changes in working capital accounts are driven solely by changes in revenues. One practical advantage of (15) is that it is easier to find variables (instruments) that are correlated with the level of accrual balances compared to the changes in these accounts. Kang and Sivaramakrishnan (1995) estimate equation (15) using two-stage least squares (2SLS) and the generalised method of moments (GMM).[10] Kang (1999) argues that this model performs better than the Jones model regardless of the sample size and using both time series and pooled estimation.[11] However, the problem with their analysis is that it does not control for unobserved effects that are either specific to the firm and constant through time, or common to all firms and time-variant − therefore, it assumes implicitly that the sample observations are independent both across firms and over time and this may well result in severe biases in their estimates, as discussed below.

2.3 Alternative Approaches

Different approaches have been employed to estimate models similar to Jones (1991) and Kang (1995), using time series, cross section or pooled data. Time series analysis has been performed at the level of a single firm and for a satisfactory length of data points (the lengthier the better), with total number of observations equal to Ti (e.g., Jones 1991; Dechow et al. 1995; Holthausen

[9] The turnover ratios are supposed to serve another purpose other than the control of expected variation in accruals. Kang and Sivaramakrishnan (1995) and Kang (1999) assume that the ratios control for firm-specificity and transform the pooled sample of firm-years into a homogeneous group of firms irrespective of industry and other specific characteristics. This is a very restrictive assumption, and even if the turnover ratios would control for observed firm-specificty, there always be specific effects that are fixed to the firm dimension that are either (i) unobserved characteristics of a company that could be allowed for in the model as additional explanatory variables, such as the quality of management, but which are not added as they would introduce additional complexity to the modelling, or (ii) unobservable factors that cannot be observed or are too difficult to proxy, such as invisible assets or undisclosed proprietary information (Itami and Roehl, 1987).

[10] See Hansen (1982).

[11] In support, Thomas and Zhang (2000) compare the accuracy of six accruals models and also find that the Kang and Sivaramakrishnan (1995) specification, despite being the least popular model at that time, is the only one that performs moderately well. Their simulations show that all models similar to equation (2) have less forecasting ability than a naïve model that assumes total accruals to be equal to −5% of the past period's total assets.

et al. 1995; Gaver et al. 1995; Kang 1999). Although time series analysis recognises the reversal properties of accruals in time, it requires a sufficiently large number of observations, which is very difficult to find in practice. It also assumes that accruals are independently generated across firms. This assumption seems unrealistic given that accruals are a result of cross-firm transactions, and one would expect that the addition of total accruals in the market (including private firms) would be an identity equal to zero. Finally time series analysis rules out the presence of unobserved factors that are common to the industry or the economy as a whole but vary through time, such as changes in the accounting standards, inflation, interest rates and other economy-wide shocks

Cross-sectional analysis has been performed at the level of industry or jurisdiction at a fixed point in time with total number of observations given by I (e.g., DeFond and Jiambalvo 1994; Subramanyam 1996; Beneish 1997; Kasnik 1999; Payne and Robb 2000; Xie 2001; Klein 2002). The use of cross-sectional data increases the sample across the spatial dimension, however, it assumes that all firms are homogeneous and unrelated to each other. Furthermore, cross-sectional analysis ignores fluctuations in the level or the change in accruals between two periods. These again are very restrictive assumptions since accruals are defined by individual firm-specific factors and are conditional to their reversal property in successive accounting periods.

Finally, pooled cross-sectional and time-series analysis has been performed on a group of firms that are commonly observed over a period of time with total number of observations equal to $N = IT_i$ (e.g., Perry and Williams 1994; Kang and Sivaramakrishnan 1995; Kang 1999). Pooling the data increases estimation efficiency but compromises on the structure of accruals in both space and time by assuming that all observations are homogeneous and independent across both dimensions.[12]

3 A Panel Data Approach

To circumvent the problems posed by analysing (i) time series data on individual firms, (ii) cross-sectional data on a sample of firms observed at a fixed point in time and (iii) pooled cross-sectional and time series data, we follow a panel data approach. Panel data methods are more appropriate for estimating equations (2) and (15) because they offer much greater flexibility in terms of controlling for unobserved heterogeneity across firms and specificity over time.[13] Furthermore, panel data methods increase the amoung of available information (in comparison to time series or cross-sectional analysis alone) by offering more observations for the same sample of firms; therefore, estimation efficiency increases.[14]

[12] Indeed, it has been shown that the market value of earnings cannot be constant across firms in neither cross-sectional nor pooled samples; Collins and Kothari (1989), Cheng et al. (1992), Beneish and Harvey (1998), Lipe, Bryant and Widener (1998) have discussed this issue − however, they all made use of time series data to perform these regressions and therefore their results are subject to the caveats of time series analysis that were described above.

[13] These advantages of panel data methods are exploited by Grambovas, Giner and Christodoulou (2006), Bradbury and Christodoulou (2008) and Christodoulou, Grambovas and McLeay (2008) who find significant heterogeneous firm-specific effects in regressions that employ accounting variables. Boynton, Dobbins and Plesko (1992) also follow a panel data approach to run regressions similar to Jones. However they ignore the estimation problems analysed in section 2.

[14] For a comprehensive econometric treatment of panel data analysis, see Hsiao (2003), Baltagi (2005) and Wooldridge (2008).

We consider the following total accruals panel data model:[15]

$$\begin{aligned}\dot{TA}_{i(\omega)t} &= \beta_{1i(\omega)}\dot{REV}_{i(\omega)t} + \beta_{2i(\omega)}\dot{REV}_{i(\omega)t-1} + \beta_{3i(\omega)}\dot{PPE}_{i(\omega)t} \\ &\quad + \alpha_{i(\omega)} + \alpha_{\omega} + \gamma_t + \gamma_{\omega t} + m_{i(\omega)t} + u_{i(\omega)t} \qquad (16)\end{aligned}$$

where $\dot{TA}_{i(\omega)t}$ denotes the deflated value of TA for firm i that belongs to industry ω at time t, for $\omega = 1, ..., \Omega$ and similarly for $\dot{REV}$ and $\dot{PPE}$. The total number of firms in a given industry is equal to $I_{(\omega)}$ and the total number of firms in all industries equals $I = \sum_{\omega=1}^{\Omega} I_{(\omega)}$. $\alpha_{i(\omega)}$ and α_{ω} denote firm-specific and industry-specific time-invariant unobserved effects respectively, while γ_t and $\gamma_{\omega t}$ reflect economy-wide and industry-wide factors respectively that change over time and influence the level of accruals. $m_{i(\omega)t}$ reflects measurement errors in capturing expecting accruals and $u_{i(\omega)t}$ is a purely idiosyncratic error term. Therefore, equation (16) allows for differences across firms and industries that are constant through time, as well as for common time-variant shocks that influence either all firms in the sample (γ_t), and specific industries only ($\gamma_{\omega t}$). Henceforth, we refer to this model as Common Time and Industry Specific Effects with Heterogeneous Coefficients (CTISE-HC).

$\beta_{1i(\omega)}$ is the coefficient of $\dot{REV}$ for firm $i \in \omega$ and similarly for the remaining coefficients. Therefore, the coefficients of $\dot{REV}$ and $\dot{PPE}$ are allowed to vary across firms, meaning that the complete set of parameters that characterise expected accruals is specific to the firm level.

Equation (16) reduces to a pooled cross-sectional time series regression by imposing the following restrictions: $\beta_{1i(\omega)} = \beta_1$, $\beta_{2i(\omega)} = \beta_2$, $\beta_{3i(\omega)} = \beta_3$, and $\alpha_{i(\omega)} = \alpha_{\omega} = \gamma_t = \gamma_{\omega} = 0$. If either of these restrictions is violated, the pooled estimator is likely to be severely biased even in large samples. Equation (16) reduces to a time series model by letting $I = 1$, in which case the sum of $\alpha_{i(\omega)}$ and α_{ω} collapses to a single intercept, $\beta_{\kappa i(\omega)}$ for the coefficient index $\kappa = 1, 2, 3$, reduces to β_{κ}, while γ_t and $\gamma_{\omega t}$ cannot be accounted for, resulting in omitted variables type of bias in the estimated coefficients. On the other hand when $T = 1$, (16) reduces to a cross-sectional model, in which case the sum of γ_t and $\gamma_{\omega t}$ reduces to a single intercept, while $\alpha_{i(\omega)}$, α_{ω} and the firm-specific slope coefficients, $\beta_{\kappa i(\omega)}$ for $\kappa = 1, 2, 3$, cannot be accounted for in estimation, resulting again in omitted variables type of bias.

We control for firm-specific heterogeneity in the slope coefficients by letting:

$$\beta_{\kappa i(\omega)} = \beta_{\kappa} + \xi_{\kappa i(\omega)},\ \xi_{\kappa i(\omega)} = \delta_{\kappa} S_{i(\omega)},\ \text{for } \kappa = 1, 2, 3. \qquad (17)$$

So equation (17) implies that the slope coefficients of $\dot{REV}$ and $\dot{PPE}$ vary across individual firms as a linear function of their size, $S_{i(\omega)}$. Indeed, there is evidence in the literature that firm size affects the level of expected accruals.[16] We proxy the size of the firm by its market value, averaged over the time period considered – that is, $S_{i(\omega)} = \overline{MV}_{i(\omega)} = \frac{1}{T}\sum MV_{i(\omega)t}$. This is a valid size measure given the focus on equities that are publicly listed on the stock exchange. In addition, $\overline{MV}_{i(\omega)}$ has the additive advantage that it is exogenous to the accounting system and it is not affected by bookkeeping rules.

Another innovation of our model compared to the standard Jones model is that we do not arbitrarily impose the coefficient of the current value of sales to be equal to minus the coefficient

[15] All variables are deflated by assets.

[16] For example, see Sloan (1996) and Xie (2001).

of its first lagged value, i.e. $\beta_1 = -\beta_2$. Rather, this restriction is tested using the observed data through linear Wald tests.[17]

Thus, applying equation (17) into (16) yields the following representation:

$$
\begin{aligned}
\dot{TA}_{i(\omega)t} \quad = \quad & \beta_{1i(\omega)t}\dot{REV}_{i(\omega)t-1} + \beta_2\dot{REV}_{i(\omega)t-1} + \beta_3\dot{PPE}_{i(\omega)t} \\
& +\delta_1 S_{i(\omega)}\dot{REV}_{i(\omega)t} + \delta_2 S_{i(\omega)}\dot{REV}_{i(\omega)t-1} + \delta_3 S_{i(\omega)}\dot{PPE}_{i(\omega)t} \\
& +\alpha_{i(\omega)} + \alpha_\omega + \gamma_t + \gamma_{\omega t} + m_{i(\omega)t} + u_{i(\omega)t} \qquad (18)
\end{aligned}
$$

Expressing the observations in the equation above in terms of deviations from time-specific averages at the industry level we obtain:

$$
\begin{aligned}
\underline{\dot{TA}}_{i(\omega)t} \quad = \quad & \beta_1\underline{\dot{REV}}_{i(\omega)t} + \beta_2\underline{\dot{REV}}_{i(\omega)t-1} + \beta_3\underline{\dot{PPE}}_{i(\omega)t} \\
& +\delta_1\utilde{\underline{\dot{REV}}}_{i(\omega)t} + \delta_2\utilde{\underline{\dot{REV}}}_{i(\omega)t-1} + \delta_3\utilde{\underline{\dot{PPE}}}_{i(\omega)t} \\
& +\underline{\alpha}_{i(\omega)} + \underline{\alpha}_\omega + \underline{m}_{i(\omega)t} + \underline{u}_{i(\omega)t} \qquad (19)
\end{aligned}
$$

where $\underline{\dot{TA}}_{i(\omega)t} = \dot{TA}_{i(\omega)t} - \frac{1}{I_{(\omega)}}\sum_{i(\omega)}^{I_{(\omega)}}\dot{TA}_{i(\omega)t} = \dot{TA}_{i(\omega)t} - \overline{\dot{TA}}_{\omega t}$ with $I_{(\omega)}$ denoting the total number of firms in industry ω, $\underline{\dot{REV}}_{i(\omega)t} = \dot{REV}_{i(\omega)t} - \frac{1}{I_{(\omega)}}\sum_{i(\omega)}^{I_{(\omega)}}\dot{REV}_{i(\omega)t}$, and $\widetilde{\underline{\dot{REV}}}_{i(\omega)t} = S_{i(\omega)}\dot{REV}_{i(\omega)t} - \frac{1}{I_{(\omega)}}\sum_{i(\omega)}^{I_{(\omega)}} S_{i(\omega)}\dot{REV}_{i(\omega)t}$. Likewise, $\underline{\alpha}_{i(\omega)} = \alpha_{i(\omega)} - \frac{1}{I_{(\omega)}}\sum_{i(\omega)}^{I_{(\omega)}}\alpha_{i(\omega)} = \alpha_{i(\omega)} - \overline{\alpha}_\omega$, and similarly for the remaining variables. Notice that the transformation has removed γ_t and γ_ω from the model, although there is still uncontrolled heterogeneity due to the presence of $\underline{\alpha}_{i(\omega)}$, $\underline{\alpha}_\omega$ in the error process and of course there is also the issue of simultaneity of the variables due to the double-entry book-keeping of financial statements.

In order to remove the time-invariant effects we transform the data by subtracting the mean of all future observations in the sample for each firm − a transformation known as 'orthogonal deviations'.[18] The motivation behind this transformation over 'first-differencing' is that it preserves sample size in panels with gaps (missing observations)[19]. Hence, the resulting model is now given by:

$$
\begin{aligned}
\underline{\dot{TA}}^*_{i(\omega)t} \quad = \quad & \beta_1\underline{\dot{REV}}^*_{i(\omega)t} + \beta_2\underline{\dot{REV}}^*_{i(\omega)t-1} + \beta_3\underline{\dot{PPE}}^*_{i(\omega)t} \\
& +\delta_1\utilde{\underline{\dot{REV}}}^*_{i(\omega)t} + \delta_2\utilde{\underline{\dot{REV}}}^*_{i(\omega)t-1} + \delta_3\utilde{\underline{\dot{PPE}}}^*_{i(\omega)t} + \underline{m}^*_{i(\omega)t} + \underline{u}^*_{i(\omega)t} \qquad (20)
\end{aligned}
$$

where $\underline{\dot{TA}}^*_{i(\omega)t} = w_{it}\left(\underline{\dot{TA}}_{i(\omega)t} - \frac{\underline{\dot{TA}}_{i(\omega)t+1}+\ldots+\underline{\dot{TA}}_{i(\omega)tT}}{T-t}\right)$ for $t = 1, ..., T-1$ and similarly for the remaining variables.[20]

Since both $\underline{\alpha}_{i(\omega)}$ and $\underline{\alpha}_\omega$ have been removed from (20), the only outstanding problem is the error in measurement in expected accruals, $\underline{m}^*_{i(\omega)t}$, and the simultaneity between all regressors

[17] Notice that in the same manner as with (7)-(8), REV and PPE can also be expressed as dependent variables in equations similar to (16). However, these are omitted here to save space.

[18] See Arellano and Bover (1995).

[19] In other words, contrary to first-differencing. which subtracts the previous observation from the contemporaneous one, orthogonal deviations subtract the average of all future available observations of a variable. As a result, no matter how many gaps, it is computable for all observations except the last for each individual, so it minimises data loss.

[20] $w_{it} = \sqrt{(T-t)/(T-t+1)}$ is a weight that equalises the variance of the transformed errors.

and the regressand. To this end, we employ the Generalised Method of Moments (GMM), which is particularly useful in this context. Specifically, the method relies on specifying a number of variables that are uncorrelated with the transformed error, $\underline{m}^*_{i(\omega)t}+\underline{u}^*_{i(\omega)t}$, but correlated with the endogenous regressors. These variables are called instruments. Contrary to the OLS method, in which identification is achieved from the assumption that the regressors are orthogonal to the errors, and therefore the expectations of the inner products or *moments* of the regressors and the errors are set to zero, in GMM the estimation problem is to find the values of the coefficients that minimise the "total extent" to which the moments of the errors and the instruments depart from zero (see Hansen 1981).

An immediate issue that arises is how to find variables that are uncorrelated with $\underline{m}^*_{i(\omega)t} + \underline{u}^*_{i(\omega)t}$ but correlated with the endogenous regressors. One advantage of panel data analysis is that this choice comes naturally from the time series dimension of the panel. In particular, lagged values of $\underline{\dot{REV}}^*_{i(\omega)t-1}$, $\underline{\dot{PPE}}^*_{i(\omega)t}$, $\widetilde{\underline{\dot{REV}}}^*_{i(\omega)t-1}$ and $\widetilde{\underline{\dot{PPE}}}^*_{i(\omega)t}$ can serve as instruments because they all are correlated with the endogenous regressors but there is no reason why they will also be correlated with the error, provided that $\underline{m}^*_{i(\omega)t} + \underline{u}^*_{i(\omega)t}$ is serially uncorrelated[21]. Hence, the GMM estimator for the slope coefficients in (20) will be unbiased in large samples.

In addition, we estimate (20) by imposing the coefficient of the current value of sales to be equal to minus the coefficient of its first lagged value:

$$\underline{\dot{TA}}^*_{i(\omega)t} = \beta\Delta\underline{\dot{REV}}^*_{i(\omega)t} + \beta_3\underline{\dot{PPE}}^*_{i(\omega)t} + \delta\Delta\widetilde{\underline{\dot{REV}}}^*_{i(\omega)t} + \delta_3\widetilde{\underline{\dot{PPE}}}^*_{i(\omega)t} + \underline{m}^*_{i(\omega)t} + \underline{u}^*_{i(\omega)t} \tag{21}$$

and a panel version of Kang's (1995) model:

$$\begin{aligned}\underline{\ddot{TA}}^*_{i(\omega)t} &= \alpha + c_1\underline{\ddot{REV}}^*_{i(\omega)t} + c_2\underline{\ddot{PPE}}^*_{i(\omega)t} + c_3\underline{\ddot{EXP}}^*_{i(\omega)t} + \\ &\quad +d_1\widetilde{\underline{\ddot{REV}}}^*_{i(\omega)t} + d_2\widetilde{\underline{\ddot{PPE}}}^*_{i(\omega)t} + d_3\widetilde{\underline{\ddot{EXP}}}^*_{i(\omega)t} + \underline{m}^*_{i(\omega)t} + \underline{u}^*_{i(\omega)t}\end{aligned} \tag{22}$$

where $\underline{\ddot{TA}}'^*_{i(\omega)t} = w_{it}\left(\underline{\ddot{TA}}_{i(\omega)t} - \frac{\underline{\ddot{TA}}_{i(\omega)t+1}+\ldots+\underline{\ddot{TA}}_{i(\omega)tT}}{T-t}\right)$ with $\underline{\ddot{TA}}_{i(\omega)t} = \ddot{TA}_{i(\omega)t} - \frac{1}{I_{(\omega)}}\sum_{i(\omega)}^{I_{(\omega)}}\ddot{TA}_{i(\omega)t} = \ddot{TA}_{i(\omega)t} - \overline{\ddot{TA}}_{\omega t}$ and $\ddot{TA}_{i(\omega)t} = \frac{TA'_{it}}{A_{it-1}}$. Likewise, $\underline{\ddot{REV}}'^*_{i(\omega)t} = w_{it}\left(\underline{\ddot{REV}}_{i(\omega)t} - \frac{\underline{\ddot{REV}}_{i(\omega)t+1}+\ldots+\underline{\ddot{REV}}_{i(\omega)tT}}{T-t}\right)$ with $\underline{\ddot{REV}}_{i(\omega)t} = \ddot{REV}_{i(\omega)t} - \frac{1}{I_{(\omega)}}\sum_{i(\omega)}^{I_{(\omega)}}\ddot{REV}_{i(\omega)t} = \ddot{REV}_{i(\omega)t} - \overline{\ddot{REV}}_{\omega t}$ and $\ddot{REV}_{i(\omega)t} = \frac{PPE_{it}\left(\frac{DEP_{it-1}}{PPE_{it-1}}\right)}{A_{it-1}}$, while $\widetilde{\underline{\ddot{REV}}} = S_{i(\omega)}\ddot{REV}_{i(\omega)t} - \frac{1}{I_{(\omega)}}\sum_{i(\omega)}^{I_{(\omega)}} S_{i(\omega)}\ddot{REV}_{i(\omega)t}$. Similar notation holds for the remaining variables with $\ddot{PPE}_{i(\omega)t} = \frac{PPE_{it}\left(\frac{DEP_{it-1}}{PPE_{it-1}}\right)}{A_{it-1}}$.and $\ddot{EXP}_{i(\omega)t} = \frac{EXP_{it}\left(\frac{NCA_{it-1}-AR_{it-1}}{EXP_{it-1}}\right)}{A_{it-1}}$.

4 Data and Statistical Description

The empirical application employs a balanced panel dataset from Datastream of $I = 650$ US firms observed over the time period 1987-2006, but due to lagged and first-differenced transformations we lose the first year and the time period is thereafter reduced to a $T = 19$ years with $N = IT = 12,350$. Equity listing consists of only primary quotes and excludes financial and unclassified equities, and the firm-panels are continuous with nonmissing multivariate data points for all variables that are employed by any of the regression models. Variables of interest include net

[21] This is a testable assumption using Hansen's 1982) test for overidentifying restrictions. If either of these errors are serially correlated, further lags of these variables can be used.

sales revenue (item 1001), depreciation, depletion and amortisation (item 1151), total operating expenses (item 1249), net income available to common (item 1751), cash and equivalents (item 2001), receivables (item 2051), total inventories (item 2101), total current assets (item 2201), property, plant and equipment (item 2501), total assets (item 2999), short term and current portion of long term debt (item 3051), total current liabilities (item 3101), total shares (item NOSH), closing price (item P) and industry group (item 6011).

To mitigate the effect of extreme data points in the analysis we apply a filter developed by Hadi (1992, 1994) for multivariate relationships, modified specifically for panel data structures (Grambovas et al., 2006; Bradbury and Christodoulou 2008).[22] The modification involves the detection of multivariate extreme firm specific averages (over Ti) for all variables employed in a regression model, so that extreme data points are identified at the level of the firm, in which case the entire panel is removed from the sample. By filtering the data from extreme firms we also hope to alleviate the problematic feature of the Jones-type of models in categorising extreme achievers as earnings management intensive firms and very low performers as non earnings management firms (Dechow et al. 1995; McNichols 2000). For each set of variables within equations (20), (21) and (22), respectively, Hadi's filter detects 39, 60 and 59 extreme firms at the 5% level of significance leaving a robust sample of 611, 590 and 591 firms each one with 19 years of data. The appropriateness of this procedure is illustrated in Figure 1, where it is contrasted to the common approach of eliminating the extreme univariate 1% of firm-year observations. It is evident that the univariate procedure severely amputates the association between variables, whereas Hadi's filter correctly recognizes those data points that are simultaneously extreme for all variables at the level of the firm. It may remove slightly less observations than the 1% approach but does not disrupt the discontinuity of the time series which in turn will create additional missing observations when fitting models with dynamic features.

Figure 2 presents an analysis of variance for all variables employed in the six models considered, i.e. the original model of Jones (1991) with and without Common Time and Industry Specific Effects with Heterogeneous Coefficients (CTISE-HC) (see equations (21) and (2) respectively), the 'decomposed' Jones model (the one that does not impose $\beta_1 = -\beta_2$ in equation (20)) with and without CTISE-HC, and the Kang and Sivaramakrishnan (1995) with and without CTISE-HC (see equations (22) and (15) respectively). The pooled variance is decomposed into that portion that is introduced due to intra-firm variability (Within) and that which is generated due to differences amongst firms (Between). First of all, it is very reassuring to see that the level of Within variation remains very high and in many cases as high as the level of the pooled variation, and this is an indication that the variables are well identified for use under a panel data model (Baum, 2006). Secondly, the levels of Between and Within variation for the variables employed in the Kang and Sivaramakrishnan (1995) model are much higher than any other model relative to Pooled, implying that turnover ratios indeed convey significant

[22] The heuristic univariate approach to extreme values is not justifiable as the observations that are removed are not necessarily 'extreme' and, secondly, the remaining data may suffer from masking and swamping problems. That is to say, one extremely leveraged observation may mask the appearance of another, or a small cluster of outliers may attract the mean and inflate the variance in such a manner that some other observations will appear as outliers, when in fact they are not. In addition, the univariate approach overlooks the association between variables and cannot guarantee robust multivariate estimates. See also Hadi and Simonoff (1993), who consider methods for detecting multiple outliers in multivariate linear (regression) models, and for a more detailed discussion over the identification of outlying observations, see Hadi (2006).

firm-specific heterogenous information. Thirdly, the introduction of CTISE-HC does not seem to distort the useful variance that is introduced by the non-demeaned variables. Table 1 gives a more detailed statistical description of these variables in terms of arithmetic means, minima and maxima.

5 Empirical Results

Table 2 reports the regression results for the Jones (1991) model and the 'decomposed' Jones model − hereafter JO and JOD respectively − using OLS, as well as the results for the Kang and Sivaramakrishnan (1995) model − hereafter KS − using the generalised method of moments.[23] All models are estimated on a pooled sample, on I separate time series and on T separate cross-sections. For the time series regressions we report only the average of the estimated coefficients of all firms. Likewise, for the cross-sectional regressions we report the yearly average of the estimated coefficients.

As we can see, for the pooled model all the variables used in JO and JOD are statistically significant at the 1% level, although the value of the R^2 coefficient is fairly small, indicating that the model has low explanatory power. Notice also that the restriction $\beta_1 = -\beta_2$ is strongly rejected on this occasion using a Wald test, meaning that JO is not supported by the data over JOD. For the KS model all variables appear to be statistically insignificant, indicating that the model is not appropriate in this context.

For the time series and cross-sectional regressions we avoid reporting the significance of coefficients, F statistics or R-squares because the results refer to averages. However, previous literature has relied upon these averages (and the average of their significance) to make inferences. This is an erroneous practice and can be misleading. For example, Figure 3 shows that when the JO model is estimated using firm-by-firm OLS time series regressions, almost half of the estimated parameters for ΔREV are insignificant at the 95% level (300 coefficients out of 649), and similarly, for the estimated coefficients of REV from the decomposed Jones model. In this sense, the KS model appears to do better in estimating firm-by-firm time series regressions but again, this is not ideal given the practical difficulties to find enough data (even a sample of 19 years is considered to be a short time series).

Table 3 reports the results obtained from estimating the panel versions of JO, JOD and KS, i.e. equations (20), (21) and (22), using the generalised method of moments. The GMM estimator in Panel A uses the second lags of the variables as instruments while the GMM estimator in Panel B uses the third lags. The null hypothesis of zero first order or second order serial correlation is rejected using the 1% level of significance. This implies that only the results reported in Panel B are valid because the second lags of the variables used as instruments in Panel A will actually be correlated with the error term. This is confirmed by Hansen's test for overidentifying restrictions; the null hypothesis that the instruments used are orthogonal to the error term is strongly rejected in Panel A. This is not the case for panel B and therefore we will focus our attention on this panel only.[24] The estimated coefficients should be interpreted as follows; the coefficient of − say − $\underline{REV}^{*KS}_{i(\omega)t}$ refers to the GMM estimate of c_1 in (22), while the

[23] In this case the first lags of the explanatory variables are used as instruments.

[24] This result also implies that there is no third order serial correlation in the error term − otherwise, Hansen's test statistic would be significant.

coefficient of $\widetilde{\underline{REV}}^{*KS}_{i(\omega)t}$ refers to the estimate of d_1 in the same equation. Hence $\widehat{c}_{1i(\omega)} = \widehat{c}_1 + \widehat{d}_1 S_{i(\omega)} = \widehat{c}_1 + \widehat{d}_1 \overline{MV}_{i(\omega)}$ according to equation (17) and given that $S_{i(\omega)}$ is proxied by $\overline{MV}_{i(\omega)}$. The average value of $\widehat{c}_{1i(\omega)}$ can then be computed as $\sum_{\omega=1}^{\Omega} \sum_{i(\omega)=1}^{N_\omega} \left(\widehat{c}_1 + \widehat{d}_1 \overline{MV}_{i(\omega)} \right) = \widehat{c}_1 + \widehat{d}_1 \sum_{\omega=1}^{\Omega} \sum_{i(\omega)=1}^{N_\omega} \overline{MV}_{i(\omega)} = .4279 + .1081 \times .7966 = .515$. On the other hand, the values of the corresponding coefficient obtained from (i) the pooled regression, (ii) the time series regressions and (iii) the cross-sectional regressions equal -7.4339, 0.5326 and 2.0528 respectively (see Table 2). This shows the extent to which these coefficients can differ when the model is mis-specified or the estimation method does not take into account the various issues analysed in Section 2.[25] Similar results apply for the remaining coefficients although it is worth noting that, interestingly, we have not found the same magnitude of difference in the estimated parameters in the Jones model.

Notice that some of the coefficients in Panel B are not statistically significant. For example, in the Jones model the coefficient of $\Delta \underline{REV}^{*}_{i(\omega)t}$ is insignificant, when theory predicts that this shouldn't be the case. However, as we can see from equation (17), what matters actually is whether at least one of β_1 or δ_1 is significant, which is true in the present case. In fact this disaggegration shows that the size of the firm is important in determining the value of the coefficient of ΔREV. By contrast, size is not important in explaining firm-specific differences in the coefficient of PPE (since δ_2 is insignificant) and therefore it appears that this coefficient is homogeneous across firms. Similar conclusions can be made in the KS model, where the coefficients of revenues and operating expenses appear to be heterogeneous but not that of PPE.

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Table 1: Descriptive Statistics

		Pooled				Between			Within		
		Mean	SD	Min	Max	SD.	Min	Max	SD	Min	Max
Jones (1991) ***N*=11,609, *I*=611, *T*=19**	TA_{it}	-0.0391	0.0824	-0.6812	1.0607	0.0290	-0.1405	0.0909	0.0772	-0.6585	0.9685
	ΔREV_{it}	0.0888	0.2448	-3.5887	4.5258	0.0781	-0.1315	0.4484	0.2320	-3.3912	4.2794
	PPE_{it}	0.4011	0.2566	0.0000	3.0459	0.2300	0.0350	1.0911	0.1142	-0.1509	2.5567
	$\underline{\tilde{TA}}^{*}_{i(\omega)t}$	-0.0012	0.0784	-0.6034	0.9237	0.0265	-0.0887	0.1054	0.0738	-0.5749	0.8522
	$\underline{\Delta REV}^{*}_{i(\omega)t}$	-0.0092	0.2322	-3.7028	4.2224	0.0737	-0.2448	0.2998	0.2202	-3.4673	4.0395
	$\underline{PPE}^{*}_{i(\omega)t}$	0.0012	0.1772	-0.6224	2.2613	0.1429	-0.4657	0.4992	0.1050	-0.5238	2.1184
	$\underline{\Delta \tilde{REV}}^{*}_{i(\omega)t}$	-0.0291	0.2176	-3.5027	3.7948	0.0825	-0.3081	0.3145	0.2014	-3.6683	3.5785
	$\underline{\tilde{PPE}}^{*}_{i(\omega)t}$	-0.0359	0.2228	-0.8652	1.8727	0.2024	-0.6402	0.9006	0.0935	-0.6898	1.5023
Jones (1991) Decomposed ***N*=11,210, *I*=590, *T*=19**	TA_{it}	-0.0387	0.0807	-0.6812	1.0607	0.0290	-0.1405	0.0909	0.0754	-0.6581	0.9689
	REV_{it}	1.2247	0.6931	0.0000	6.7689	0.6082	0.1310	4.2005	0.3332	-0.7308	6.1664
	REV_{it-1}	1.1365	0.6251	0.0205	5.1893	0.5693	0.1357	3.8950	0.2593	-0.6893	3.5317
	PPE_{it}	0.4039	0.2549	0.0000	3.0459	0.2281	0.0350	1.0911	0.1143	-0.1481	2.5596
	$\underline{\tilde{TA}}^{*}_{i(\omega)t}$	-0.0009	0.0766	-0.6034	0.9237	0.0264	-0.0887	0.1054	0.0719	-0.5746	0.8420
	$\underline{REV}^{*}_{i(\omega)t}$	-0.0630	0.5746	-1.8721	4.6170	0.4835	-1.6636	1.9347	0.3111	-2.2891	4.6470
	$\underline{REV}^{*}_{i(\omega)t-1}$	-0.0543	0.5123	-1.6722	3.2180	0.4509	-1.5229	1.8697	0.2438	-1.6510	2.2362
	$\underline{PPE}^{*}_{i(\omega)t}$	0.0020	0.1768	-0.6224	2.2613	0.1424	-0.4657	0.4992	0.1050	-0.5230	2.1192
	$\underline{\tilde{REV}}^{*}_{i(\omega)t}$	-0.2209	0.7101	-3.1127	4.4967	0.6526	-2.3749	2.6851	0.2812	-2.6456	3.9567
	$\underline{\tilde{REV}}^{*}_{i(\omega)t-1}$	-0.1928	0.6359	-3.0102	2.7940	0.5987	-2.2438	2.4494	0.2156	-1.8763	1.7712
	$\underline{\tilde{PPE}}^{*}_{i(\omega)t}$	-0.0368	0.2149	-0.8652	1.5594	0.1948	-0.6402	0.6180	0.0911	-0.6604	1.5014

cont…/ Table 1: Descriptive Statistics

Kang and Sivaramakrishnan (1995) ***N*=11,229, *I*=591, *T*=19**	TA'_{it}	0.1141	0.1785	-0.6493	1.0491	0.1583	-0.2162	0.5481	0.0827	-0.4255	0.9514
	REV^{KS}_{it}	0.1776	0.1194	0.0000	0.9606	0.1023	0.0000	0.5633	0.0616	-0.1955	0.7638
	PPE^{KS}_{it}	0.0516	0.0277	-0.0098	0.5994	0.0204	0.0083	0.1573	0.0188	-0.0526	0.5569
	EXP^{KS}_{it}	-0.1697	0.1247	-1.7570	0.7240	0.0972	-0.5461	0.0325	0.0781	-1.6127	0.8454
	$\underline{\tilde{TA}}'^{*}_{i(\omega)t}$	0.0030	0.1451	-0.8168	0.7969	0.1239	-0.3176	0.5548	0.0756	-0.4962	0.7232
	$\underline{REV}^{*KS}_{i(\omega)t}$	-0.0042	0.0983	-0.2729	0.7244	0.0791	-0.2522	0.3180	0.0584	-0.4075	0.5522
	$\underline{PPE}^{*KS}_{i(\omega)t}$	0.0000	0.0256	-0.0705	0.4986	0.0183	-0.0468	0.0769	0.0179	-0.0996	0.4635
	$\underline{EXP}^{*KS}_{i(\omega)t}$	0.0039	0.1076	-1.5514	0.9867	0.0753	-0.3085	0.2349	0.0769	-1.3860	1.0311
	$\underline{\tilde{REV}}^{*KS}_{i(\omega)t}$	-0.0261	0.1131	-0.3887	1.0415	0.0984	-0.2997	0.3765	0.0559	-0.3789	0.9450
	$\underline{\tilde{PPE}}^{*KS}_{i(\omega)t}$	-0.0067	0.0334	-0.1073	0.4777	0.0289	-0.0794	0.1020	0.0167	-0.1108	0.4086
	$\underline{\tilde{EXP}}^{*KS}_{i(\omega)t}$	0.0250	0.1162	-1.1027	0.8757	0.0939	-0.3810	0.2871	0.0685	-0.8117	0.8805

Note: Pooled indicates the pooling level of firm-year observations *N*, Between the level of firm-means *I*, and Within the intra-firm level (within *T*). Mean indicates the arithmetic average, SD the standard deviation, Min the minimum and Max the maximum. The statistics for the Jones (1991), Jones (1991) Decomposed and Kang and Sivaramakrishnan (1995) models are computed over samples that are free of multivariate outliers. *TA* is total accruals flow (equation 1), *TA'* is total accruals balance (equation 14), ΔREV is change in revenue, *REV* is current revenue, *PPE* is property plant and equipment and *EXP* is operating expenses. The index *it* indicates a firm-year observation, and (ω) the industry within which is firm is assigned to. *KS* indicates a variable specific to the Kang and Sivaramakrishnan (1995) model (i.e. denoting multiplication with lagged turnover ratios), an underlined coefficient the inclusion of Common-Time Industry Specific Effects (CTISE), a hyphen ~ the inclusion of Heterogeneous Coefficients (HC) and * transformation through orthogonal deviations. All variables are deflated by the beginning of the year total assets A_{it-1}.

Table 2: Estimates from Pooled Ordinary Least Squares

	Pooled			Time Series (*averages*)			Cross-Sectional (*averages*)		
	Jones (1991)	Jones (1991) Decomposed	KS (1995)	Jones (1991)	Jones (1991) Decomposed	KS (1995)	Jones (1991)	Jones (1991) Decomposed	KS (1995)
α_0	-0.0409 ***	-0.0379 ***	0.0455	-0.0537	-0.0710	-0.2367	-0.0187	-0.0052	0.3267
ΔREV_{it}	0.1255 ***			0.1395			0.1143		
PPE_{it}	-0.0521 ***	-0.052 ***		0.0520	0.0462		-0.0533	-0.0535	
REV_{it}		0.1103 ***			0.1401			0.1024	
REV_{it-1}		-0.1122 ***			-0.1411			-0.1046	
REV_{it}^{KS}			-7.4339			0.5326			2.0528
PPE_{it}^{KS}			1.5828			-0.3039			-2.0613
EXP_{it}^{KS}			-9.2876			1.6718			1.5012
MV_{it}			0.0071			-0.0017			-0.1930
Industry	*yes*	*yes*	*yes*	*no*	*no*	*No*	*no*	*no*	*No*
Obs.	11695	11606	10959	17.99	17.91	17.07	615.94	611.50	608.83
F	82.6102 ***	82.3293 ***		*n/a*	*n/a*		*n/a*	*n/a*	
R^2	0.1504	0.156	.	*n/a*	*n/a*		*n/a*	*n/a*	
$\chi 2$			481.1244			*n/a*			*n/a*
Wald p		2.95 ***			*n/a*			*n/a*	

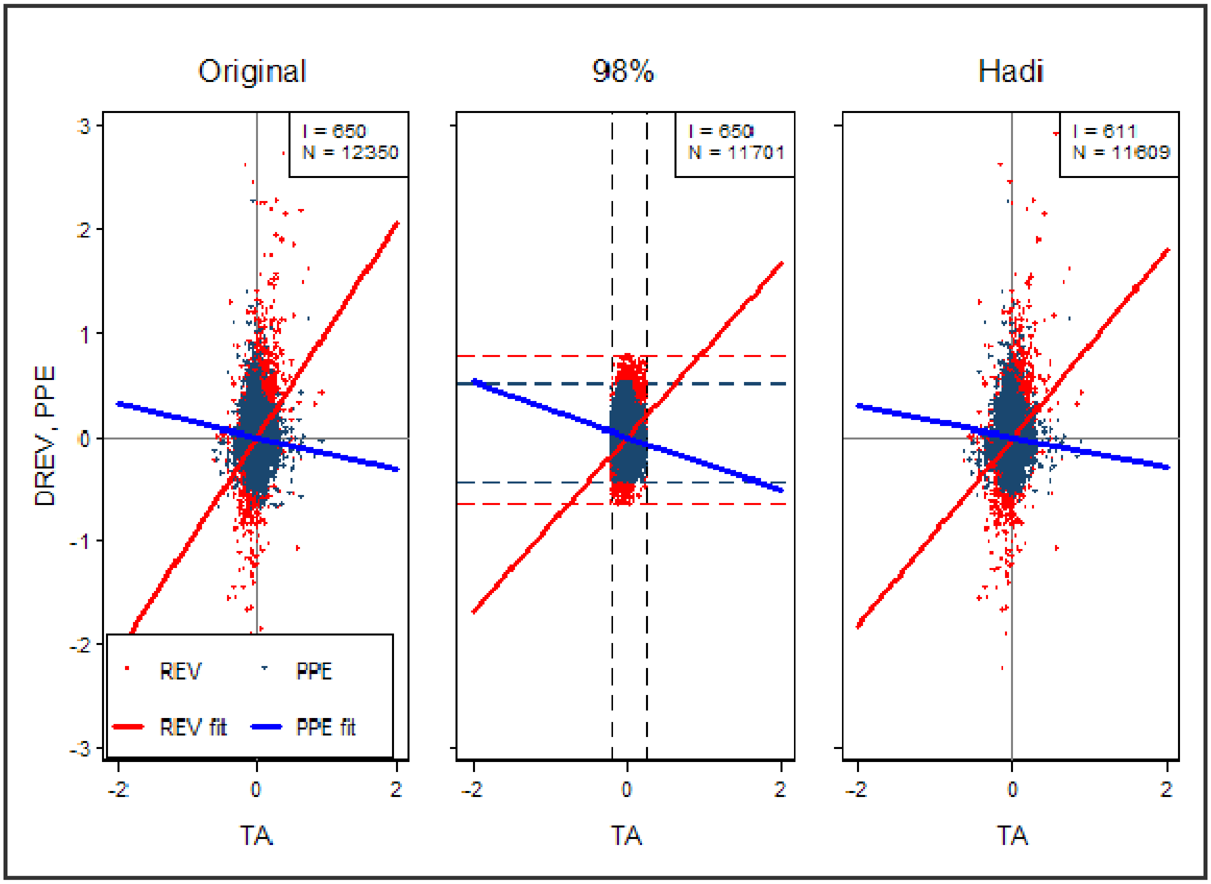
Note: The Jones (1991) and the Jones (1991) Decomposed model are estimated through OLS. The Kang and Sivaramakrishnan (KS, 1995) model is estimated through IV-GMM, with the first order lags of all explanatory variables as instruments. The reported coefficients of these three models are estimated for time series analysis on firm-specific time periods T_i, and for cross sectional analysis on year-specific cross-sections I_t (their significance is suppressed as its average is not an appropriate indicator). The significance of coefficients for pooled analysis is examined at the levels of 10% (*), 5% (**), and 1% (***). Industry indicates whether industry-specific intercepts where included in the model (*yes*), *Obs*. the number of observations, *F* the F-statistic for overall model significance, R^2 the goodness of fit, $\chi 2$ the chi-square test for overall model significance, and *Wald p* the p-value for the linear Wald test $REV_{it} + REV_{it-1} = 0$. *n/a* indicates not applicable. ΔREV is change in revenue, *REV* is current revenue, *PPE* is property plant and equipment and *EXP* is operating expenses. The index *it* indicates a firm-year observation and *KS* indicates a variable specific to the Kang and Sivaramakrishnan (1995) model (i.e. denoting multiplication with lagged turnover ratios). All variables are deflated by the beginning of the year total assets A_{it-1}.

Table 3: Estimates Panel Data Model of Common-Time Industry Specific Effects with Heterogeneous Coefficients

	GMM with Second Order Lagged Instruments			GMM with Third Order Lagged Instruments		
	Jones (1991)	Jones (1991) Decomposed	KS (1995)	Jones (1991)	Jones (1991) Decomposed	KS (1995)
$\underline{\Delta REV}^{*}_{i(\omega)t}$	-0.0253			0.0395		
$\underline{PPE}^{*}_{i(\omega)t}$	-0.0438	-0.0254		-0.0849 ***	-0.0703 **	
$\underline{\Delta \tilde{REV}}^{*}_{i(\omega)t}$	0.0812 ***			0.0745 ***		
$\underline{P\tilde{P}E}^{*}_{i(\omega)t}$	0.0077	-0.0065		0.0266	0.024	
$\underline{REV}^{*}_{i(\omega)t}$		-0.0344			0.0538 **	
$\underline{REV}^{*}_{i(\omega)t-1}$		0.0532 *			-0.0456	
$\underline{R\tilde{E}V}^{*}_{i(\omega)t}$		0.0725 **			0.0767 ***	
$\underline{R\tilde{E}V}^{*}_{i(\omega)t-1}$		-0.067			-0.0883 **	
$\underline{REV}^{*KS}_{i(\omega)t}$			0.9617 ***			0.4279 ***
$\underline{PPE}^{*KS}_{i(\omega)t}$			-1.6609 ***			-1.6922 ***
$\underline{EXP}^{*KS}_{i(\omega)t}$			0.3825 ***			-0.4322 ***
$\underline{R\tilde{E}V}^{*KS}_{i(\omega)t}$			0.1714 *			0.1081 **
$\underline{P\tilde{P}E}^{*KS}_{i(\omega)t}$			0.0315			-0.0348
$\underline{E\tilde{X}P}^{*KS}_{i(\omega)t}$			-0.01			0.0687 *
N	10998	10620	10638	10998	10620	10638
I	611	590	591	611	590	591
Instruments	86	86	120	81	81	113
$AR(1)$	-42.9609 ***	-41.2879 ***	-31.1009 ***	-46.4867 ***	-42.9518 ***	-6.8217 ***
$AR(2)$	3.0757 ***	3.289 ***	10.2205 ***	3.4862 ***	4.2075 ***	-4.3806 ***
Hansen	102.1772 **	105.96 **	196.01586 ***	87.668539	87.805832	83.58697
χ^2	19.2266	22.411	998.7632	39.1537	31.8527	450.8117
Wald		8.35 ***			0.15	

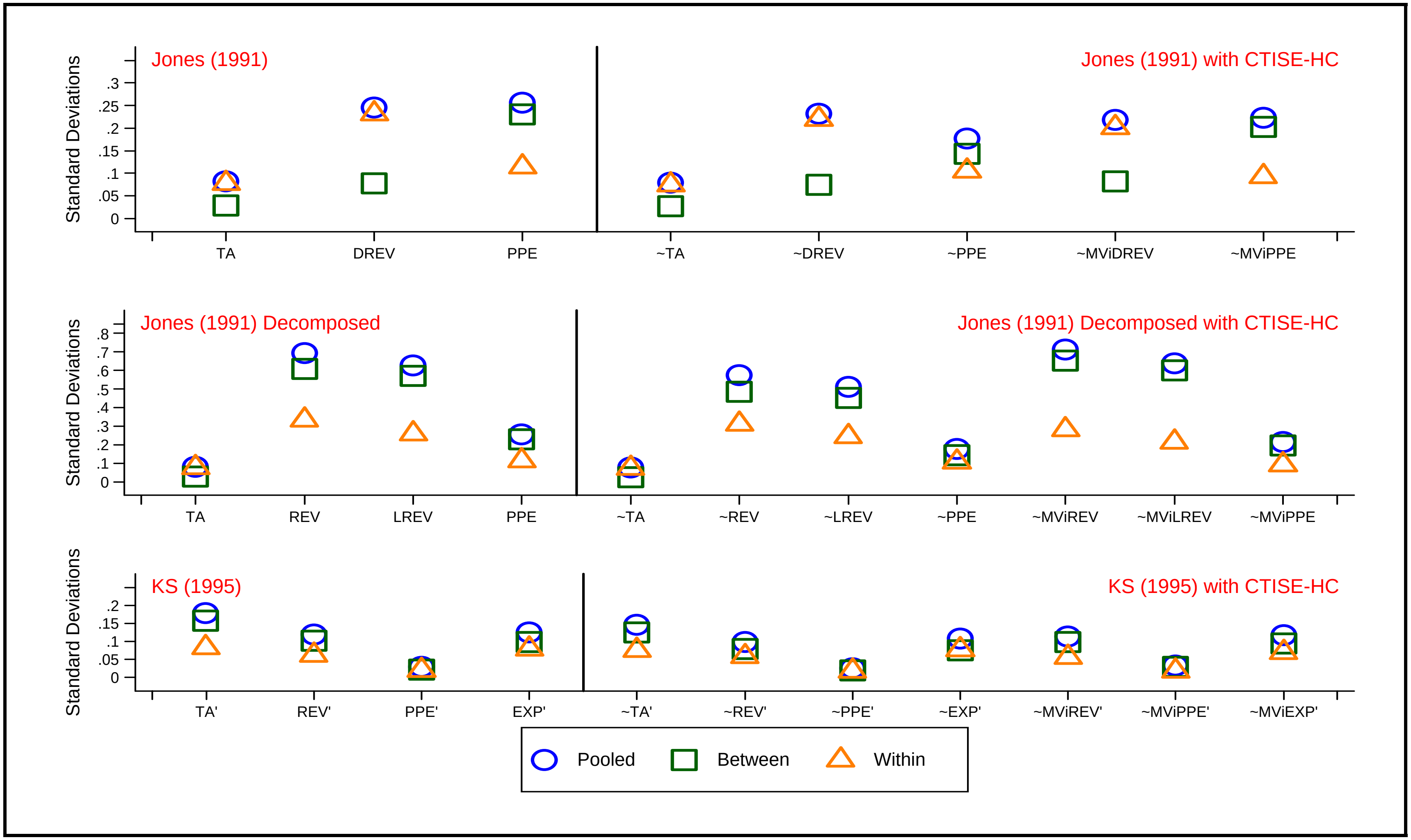
Note: ΔREV is change in revenue, REV is current revenue, PPE is property plant and equipment and EXP is operating expenses. The index it indicates a firm-year observation, and (ω) the industry within which is firm is assigned to. KS indicates a variable specific to the Kang and Sivaramakrishnan (1995) model (i.e. denoting multiplication with lagged turnover ratios), an underlined coefficient the inclusion of Common-Time Industry Specific Effects (CTISE), a hyphen ~ the inclusion of Heterogeneous Coefficients (HC) and * transformation through orthogonal deviations. All variables are deflated by the beginning of the year total assets A_{it-1}. Significance is examined at the levels of 10% (*), 5% (**), and 1% (***).

Figure 1: Robustness against Outliers



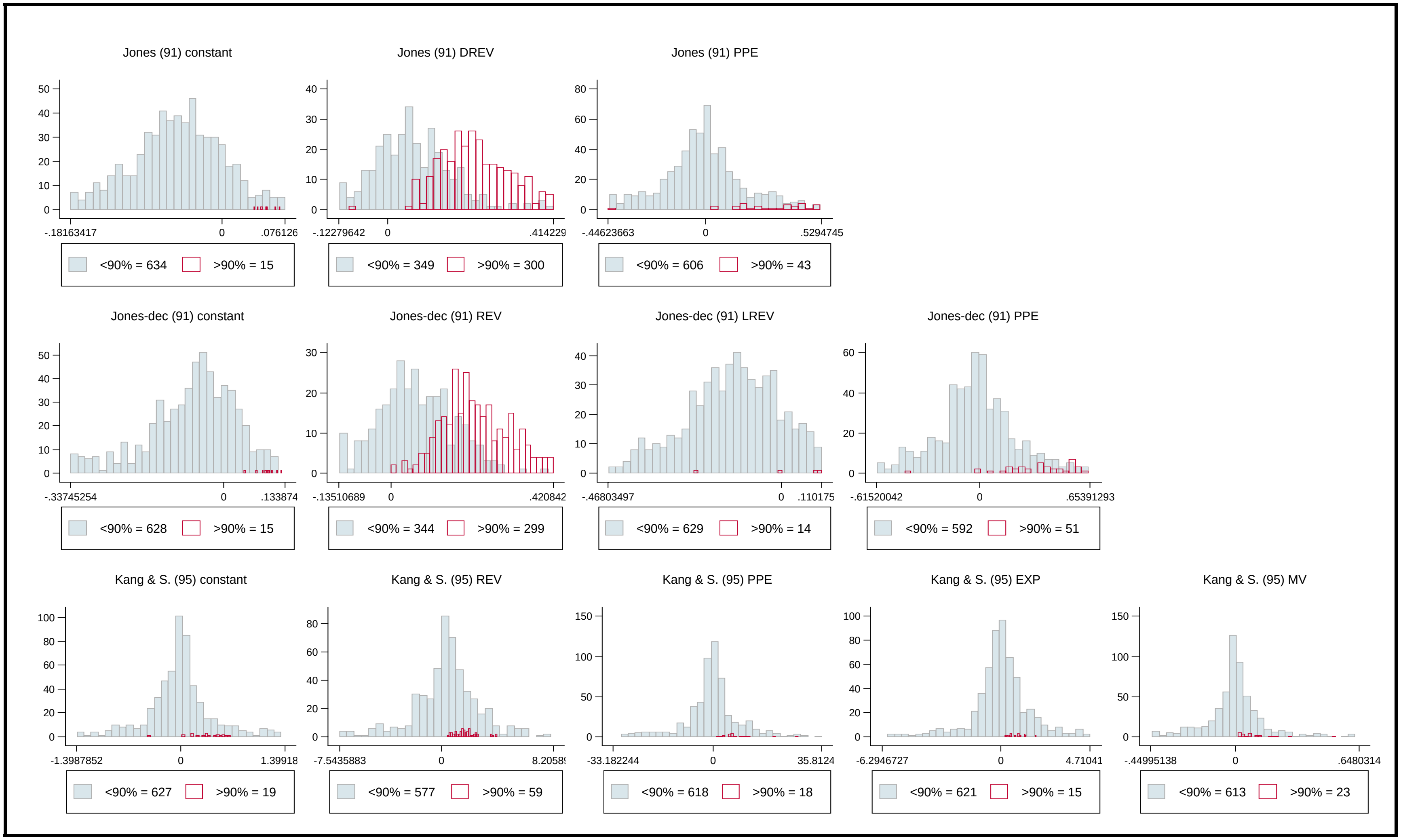
Note: The scatter graphs plot the bivariate relationships between the covariates of the change in revenue REV_{it} / A_{it-1} and the gross level of property plant and equipment PPE_{it} / A_{it-1}, against the dependent variable of total accruals TA_{it} / A_{it-1}, i.e. those employed in the original Jones (1991) model. The lines plot the respective linear fits. To assist visual representation, the *x*-axis is truncated to range [-2,2] and the *y*-axis to range [-3,3]. The left hand graph plots the Original sample. The central graph plots the remaining data points in the middle 98% of the distribution, *i.e.* following the elimination of the univariate lower and upper 1% variation for the three variables. The right hand graph plots the remaining firms following the outlier filter proposed by Hadi (1992, 1994) for detecting multivariate outliers on all three variables simultaneously. $N=IT_i$ indicates the number of firm-year observations, and I the number of firms in each sample.

Figure 2: Analysis of Variance



Note: Pooled Standard Deviation is dissagregated into Within (intra-firm) and Beween (across firms), for each one of the following models: the original model of Jones (1991) with and without Common Time Industry Specific Effects with Heterogeneous Coefficients (CTISE-HC), the Jones (1991) Decomposed with and without CTISE-HC, and the Kang and Sivaramakrishnan (KS, 1995) with and without CTISE-HC. TA is total accruals as calculated by equation (1), DREV is change in revenue, PPE is property plant and equipment, REV is current revenue and LREV is lagged revenue. TA' is total accruals as calculated by equation (14), and REV', PPE' and EXP' indicate the variables employed by KS (1995). A variable followed by a hyphen ~ indicates the inclusion of CTISE, where MVi indicates multiplication with the mean of Market Value that is specific for firm *i* (i.e. allowing for HC). All variables are deflated by the beginning of the year total assets.

Figure 3: Estimated Coefficients from Firm-by-Firm OLS Time Series



Note: The histograms represent the estimated values from OLS time series for the coefficients of the Jones (1991) model (first row) and the Jones (1991) decomposed model (second row), as well as the IV-GMM time series for the Kang and Sivaramakrishnan (1995) model (third row). To assist visual representation we restrict the range of values to the middle 90%. The gray shade histograms indiate the distribution for the significant coefficients at the 90% level, and the outlined histograms the distribution of coefficients that are insignificant at the 90% level. <90%=*I* and >90%=*I* indicates the number of firm-specific time series regresisons that are insignificant or significant at the 90% level. constant indicates the intercept of each model, where each of REV (revenue), DREV (first-differenced revenue), REV (current revenue), LREV (lagged revenue), PPE (property, plant and equipment), EXP (expenses) and MV(market value) are specific to each model (see discussion in core text).