The Effect of Financing Changes on Discretionary Accruals Estimation

Jorge Manuel Afonso Alves (*)
UNIAG /OBEGEF/ Escola Superior de Tecnologia e Gestão
Instituto Politécnico de Bragança
Campus de Santa Apolónia – Apartado 134. 5301-857 Bragança/Portugal
Tel: 00.351.273.303.121; Fax: 00.351.273.313.051
E-mail: jorge@ipb.pt

José A. C. Moreira
Faculdade de Economia da Universidade do Porto / CEF.UP / OBEGEF
Rua Roberto Frias - 4200-464 Porto / Portugal
Tel: 00.351.225 571 272; Fax: 00.351. 225 505 050
E-mail: jantonio@fep.up.pt.

(*) Contact Author.

This work is funded by National Funds through the Foundation for Science and Technology under the project UID / GES / 04752/2016.

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Abstract:

This study discusses the impact of financing changes (banks, shareholders loans, equity increases and other equity instruments) on accruals models, and discretionary accruals estimates. It pursues a threefold objective. Firstly, to show analytically how the occurrence of such changes affects discretionary accruals estimation. Secondly, to analyse empirically whether different accruals models - Jones (1991), Dechow and Dichev (2002), and McNichols (2002) - reflect in a similar way the impact of changes in corporate financing. Thirdly, compare for the Portuguese context the efficiency of the proposed methodology to Shan, Taylor and Walter (2013), in order to assess the relative performance of each one. Empirical evidence shows that the measurement error induced by not well-specified accruals models is affected by the sign of financing changes, being different for positive and negative changes; all models reflect in a similar way the impact of changes in corporate financing; and for the Portuguese context, the matched-firm approach on financing changes, intended to mitigate the problem caused by such changes on discretionary accruals, does not work well.

Keywords: Accruals models, financing changes, SME, Portugal

1. Introduction

The literature on earnings management studies is vast (e.g., Ronen & Yaari, 2008). In most cases, they use discretionary accruals as a proxy for earnings manipulation, estimated with a model where accruals are the dependent variable and the firm's change in revenues (e.g., Jones, 1991) or cash flows (e.g., Dechow & Dichev, 2002) are the main independent variables.

One of the criticisms most often addressed to such models is that they omit explanatory variables correlated with the accruals (Ball & Shivakumar, 2008; Liu, 2008; Moreira, 2006; Shan et al., 2013). This omission may induce measurement error in estimating discretionary accruals, leading to situations where a firm is classified as manipulative when, in fact, it may not have manipulated earnings (e.g., Ball & Shivakumar, 2008; Chen, Hribar & Melessa, 2018; Dechow, Hutton, Kim & Sloan, 2012; Liu, 2008; Shan et al., 2013). An obvious consequence of such a situation is the discredit of studies that use discretionary accruals as a driving component of their analyses.

In many studies, authors have attempted to find solutions to solve the problem caused by omission of explanatory variables in accruals models (e.g., Dechow et al., 2012; Shan et al., 2013). However, the solutions they propose are not always applicable to all cases. This happens, for example, with the solution proposed by Dechow et al. (2012), according to which we need to know exactly the periods accruals are managed and reversed. Gerakos (2012) recognize that such approach is only applicable when one uses a sample of firms with known manipulation. Other solutions, as the matched-firm approach presented by Kothari, Leone and Wasley (2005), only mitigates the misspecifications for samples where the omitted variable presents extremes values, but can exaggerate misspecification in other situations (Dechow et al., 2012).

The current study discusses the impact of corporate financing changes, hereafter financing changes (bank and shareholders loans, equity increases and other equity instruments), on accruals models, and discretionary accruals estimates. It proposes a way to tackle with the omission of the debt change variable in accruals models, in order to control the measurement error induced by such omission. Somehow, the current paper follows a research line similar to that of Shan et al. (2013), but it tests a different economic and entrepreneurial context, and uses a diverse methodology. Based on Dechow et al. (2010) findings, that the measurement error in estimating discretionary accruals tends to be related to industry characteristics and the contexts where firms operate, we expect the solution proposed by Shan et al. (2013) not to work in the Portuguese economic and entrepreneurial context underlying our research. We then will replicate Shan et al. (2013) methodology to test whether it is applicable in such a context.

Our study adds to recent studies that seek to propose new approaches to estimate discretionary accruals (e.g., Gerakos, 2012; Kim, Kim, Kwon & Lee, 2015; Marai & Pavlović, 2014). Thus, our main motivation is to make a contribution to improve existing accruals models.

The empirical methodology adopted is similar to that used by Moreira (2006), based on a comparative static approach. Two versions of each model are estimated, differentiating by the consideration in one of them of a variable controlling for financing changes. The differential measurement error allows conclusions about the quality of the model specification and its consequences for accruals estimation. In a first moment a graphic analysis is carried out; afterwards, and to test the robustness of the results, an analysis based on simulations is performed (e.g., Dechow, Sloan & Sweeney, 1995; Hribar & Collins, 2002; Kothari et al., 2005; Shan et al., 2013).

The present study makes three main contributions to the literature. Firstly, it shows that the measurement error induced by models poor specification is affected by the sign of financing changes. Secondly, the measurement error exists regardless of the size and sign of those changes. Finally, the results of the study add to the scarce literature on the estimation of accruals in a context of non listed small and medium firms, and shows that a matched-firm approach on financing changes likewise Shan et al. (2013) does not work in such a context.

The study contains five additional sections. The second section discusses analytically the accruals impact arisen from financing changes. The following section introduces the methodology to be used and some descriptive statistics. The empirical results are presented and discussed in section four. Finally, the main conclusions, contributions and limitations of the study are discussed.

2. Financing Changes and Accruals Measurement Error

Accruals definition and its correlation with financing changes

Let us begin by introducing a balance sheet definition of total accruals (ACC) (e.g., Dechow et al., 1995; Healy, 1985; Jones, 1991; McNichols, 2002):

$$\mathrm{ACC} = (\Delta\mathrm{CA} - \Delta\mathrm{CL} - \Delta\mathrm{CASH} + \Delta\mathrm{CMD} - \mathrm{DA}) \qquad [1]$$

where the symbol Δ stands for change, CA is current assets; CL is current liabilities; CASH is cash; CMD is current maturities of long-term debt; and DA is the depreciation and amortization expense.

There are authors (e.g., Peasnell, Pope & Young, 2000; Young, 1999) that argue that the depreciation and amortization expense, due to its visibility and predictability, is essentially non-discretionary and therefore have limited potential as an instrument of earnings management. Hence, they suggest that accruals estimation should use working capital accruals (WCA) instead of ACC, which are obtained by adding DA to the above equation (1).

Rearranging the variables, changes in current assets net of changes in cash is defined as ΔNCA = ΔCA - ΔCASH, and changes in current liabilities net of changes in current maturities of long-term debt as ΔNCL = ΔCL - ΔCMD. It is then possible to write:

$$\mathrm{WCA} = (\Delta\mathrm{NCA} - \Delta\mathrm{NCL}) \qquad [2]$$

The relationship between WCA and changes in corporate financing is developed based on the balance sheet identity (e.g., Dechow, Richardson & G.Sloan, 2008; Richardson, Sloan, Soliman & Tuna, 2005; Shan et al., 2013):

$$Total\ Assets\ (TA) = Total\ Liabilities\ (TL) + \ Total\ Owners\ Equity\ (TOE) \qquad [3]$$

TA can be decomposed into net current asset (NCA) plus other assets (OA). In turn, TL can be decomposed into net current liabilities (NCL), financing (FIN) and other liabilities (OL). Finally, TOE, also a source of corporate financing, can be decomposed into equity and other equity instruments (EOEI), and other equity (OE). Thus, expression (3) can be rewritten as follows:

$$\mathrm{NCA} + \mathrm{OA} = \mathrm{NCL} + \mathrm{FIN} + \mathrm{OL} + \mathrm{EOEI} + \mathrm{OE} \qquad [4]$$

Isolating NCA and NCL on the left side of the expression and merging all sources of financing into one variable, which is designed as total financing FINT = FIN + EOEI is possible to obtain the following expression:

$$\mathrm{NCA} - \mathrm{NCL} = \mathrm{FINT} + \mathrm{OL} + \mathrm{OE} - \mathrm{OA} \qquad [5]$$

Applying changes to this expression one gets:

$$\mathrm{WCA} = \Delta\mathrm{FINT} + \Delta\mathrm{OL} + \Delta\mathrm{OE} - \Delta\mathrm{OA} \qquad [6]$$

It is now obvious that ΔFINT is a determinant of WCA.[1]

In general, the accruals models include a set of independent variables (V_1, $V2$,…, Vn) that explain the dependent variable, ACC or WCA. For the purpose of the current discussion, let us assume it is WCA. It can then be written as $WCA = f(V_1, V_2, \ldots, V_n)$, and an accruals model in the following way (e.g., Moreira, 2006):

$$\mathrm{WCA_t} = \sum_{k,j=1}^{n} \beta_k \,.\, \mathrm{V_j} \qquad [7]$$

where β_k is a set of estimated parameters; V_j are explanatory variables, specific of each model, but assumed to be related to WCA.[2] Most common accruals models do not contain one or more explanatory variables that control for financing changes (bank and shareholders loans, equity increases and other equity instruments). However, as Ball and Shivakumar (2008) suggest, when a firm increases its financing it tends to use the proceedings to increase inventories and accounts receivable as a result of an expansion of its operations. In such cases, increases in inventories and in receivables imply positive changes in WCA beyond those directly related to

[1] Recent studies show that there is a positive and statistically significant correlation between WCA and ΔFINT. For example, in Shan et al. (2013) the correlation between WCA and ΔFINT is 0.22 and 0.17 for Spearman and Pearson coefficients correlation, respectively; in Zhang (2007) it is 0.211 and 0.322.

[2] For example, in the Jones (1991) Model (JM) they correspond, essentially, to the change in revenues; in Dechow and Dichev (2002) Model (DDM) they correspond to cash flows from operations in periods *t-1*, *t* and *t+1*.

the change in revenues. The opposite situation will tend to occur when a firm undertakes a negative financing change, reducing its financing level (e.g., Zhang, 2007). Hence, a positive financing change (ΔPF) is expected to lead to an increase in WCA and a negative one (ΔNF) to a decrease. Defining $\overline{\overline{\mathrm{WCA}}}$ as total accruals in a "steady state", characterized by no changes, then if during the analysis period a given firm faces situations of ΔPF or ΔNF, it is possible to write the following inequality:

$$\mathrm{WCA}_{\Delta\mathrm{NF}} < \overline{\overline{\mathrm{WCA}}} < \mathrm{WCA}_{\Delta\mathrm{PF}} \quad [8]$$

where $WCA_{\Delta NF}$ ($WCA_{\Delta PF}$) is total accruals when in the period there are only negative (positive) financing changes.

This relationship shows the impact of these changes on WCA according to their nature (positive/negative). However, as mentioned above, because most commonly used accruals models (e.g., Ball & Shivakumar, 2006; Dechow & Dichev, 2002; Jones, 1991; Peasnell et al., 2000) do not incorporate any explanatory variable directly related to such changes then accruals estimates may contain a measurement error.

The evidence suggests thus that accruals models are not well-specified, and thus should be improved (e.g. Shan et al., 2013; Young, 1999).

Measurement error in estimating discretionary accruals

Taking model (7) and assuming only one explanatory variable (e.g. change in revenue, V) and an independent term α_0 it comes:

$$\mathrm{WCA}_t = \alpha_0 + \beta_1 V_t + \delta_t \quad [7.1]$$

where δ is the residual term of the equation. Taking into account the above discussion on the asymmetric impact of financing changes on the equation, one has to conclude that the model is not well-specified and suffers from an omitted uncorrelated explanatory variables bias (e.g., Johnston, 1984). It misses one or more explanatory variables that explain the impact of financing changes on the dependent variable (WCA_t). The econometric consequences of such a problem are well-known: the estimated coefficients of the explanatory variables will not be biased (in this case $\hat{\beta}_1$), but the independent term will absorb the mean effect of the omitted variables and the error term will absorb the remaining (Johnston, 1984).

For a better understanding of these consequences, let's assume $\hat{\alpha}_0^{\Delta PF}$ is the independent term when there are only ΔPF in the estimation period; $\hat{\alpha}_0^{\Delta NF}$ when there are only ΔNF; and $\hat{\alpha}_0^{\Delta PF/\Delta NF}$, the "average" independent coefficient, when there are simultaneously ΔPF and ΔNF. The "average" coefficient will be lower than $\hat{\alpha}_0^{\Delta PF}$ and higher than $\hat{\alpha}_0^{\Delta NF}$, and one may write the following relationship:

$$\hat{\alpha}_0^{\Delta NF} < \hat{\alpha}_0^{\Delta PF/\Delta NF} < \hat{\alpha}_0^{\Delta PF} \quad [9]$$

Thus, in the most common situation, when there are both types of financing changes during the period,[3] the independent term tends to be an "average" coefficient that does not fit either ΔPF or ΔNF situations.

The measurement error is now easy to predict if one takes into account the "average" coefficient and the residual of the equation (δ), the so called discretionary accruals (DAC). Based on equation (7.1), the residual can be written as:

$$\mathrm{WCA}_t - \left(\hat{\alpha}_0 + \hat{\beta}_1 V_t\right) = \delta_t = \mathrm{DAC}_t \quad [10]$$

where the expression in parentheses equals the estimated "normal" value of WCA $\left(\widehat{\mathrm{WCA}}_t\right)$.

Let's define the measurement error (ERR) as the difference between DAC estimates obtained with a model that controls (C) for the financing changes (DAC_C), and DAC estimates of a model like equation (10) that does not control (NC) for such changes (DAC_{NC}). The error can thus be written as ERR = DAC_C - DAC_{NC}. Taking into account the effects discussed above and expression (9), it is possible to establish the following prediction for the measurement errors:

$$\begin{cases} \mathrm{ERR}_{\Delta\mathrm{PF}} < 0 \\ \mathrm{ERR}_{\Delta\mathrm{NF}} > 0 \end{cases} \quad [11]$$

Thus, if accruals estimation is not controlled for financing changes then one may expect that DAC estimations are overestimated for firm-years having ΔPF, and underestimated for those having ΔNF.

[3] If we think that the model is regressed cross-sectionally for a single year but there are firms facing ΔPF and others facing ΔNF the effects are similar to those discussed hereafter.

3. **Research Design and Sample Selection**

Methodology

As mentioned above, one purpose of the current study is to test the existence of DAC measurement errors caused by the lack of control for financing changes. We test the Jones (1991) model (JM), Dechow and Dichev (2002) model (DDM) and McNichols (2002) model (MM).

The methodology is identical to the one used by Moreira (2006), based on a comparative static approach that compares accruals estimates obtained with two versions of the models: the current version, that does not control (NC) the effect of financing changes and a version that controls (C) for such changes. The models are defined as follows:

$$\text{NC: } WCA_t = \propto_0 + \sum_{k,j=1}^{n} \beta_k . V_j + \xi_t \quad [12]$$

$$\text{C: } WCA_t = \propto_0 + \sum_{k,j=1}^{n} \beta_k . V_j + \gamma_1 . C_t + \mu_t \quad [13]$$

where WCA is working capital accruals; V_j is a set of independent variables underlying the basic model[4]; C_t is a dummy variable that intends to control for the effect of $\Delta FINT_t$ (assumes value 1 if the financing change is positive, 0 if negative[5]); $\propto$, β, γ are parameters; and ξ and μ are the residuals of the regressions.

The tow full versions of each used model are the following:

$$\text{JM}\begin{cases} NC \Rightarrow WCA_t = \alpha_0 + \beta_1 INV_t + \beta_2 \Delta REV_t + \xi_t \\ C \Rightarrow WCA_t = \alpha_0 + \beta_1 INV_t + \beta_2 \Delta REV_t + \theta_1 C_t + \mu_t \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots \ldots\ldots\ldots\ldots\ldots\ldots [14]$$

$$\text{DDM}\begin{cases} NC \Rightarrow WCA_t = \alpha_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \xi_t \\ C \Rightarrow WCA_t = \alpha_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \theta_1 C_t + \mu_t \end{cases} \ldots\ldots \ldots [15]$$

$$\text{MM}\begin{cases} NC \Rightarrow WCA_t = \alpha_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \beta_4 \Delta REV_t + \xi_t \\ C \Rightarrow WCA_t = \alpha_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \beta_4 \Delta REV_t + \theta_1 C_t + \mu_t \end{cases} \ldots \ldots [16]$$

where,

WCA_t **-** Working capital accruals in year$_t$ defined as changes in current assets less changes in current liabilities less changes in cash plus changes in current maturities of long-term debt;

INV_t – Is the inverse of average total assets of year$_t$;

ΔREV_t – Change in revenue in year$_t$;

CFO_t - Cash flows from operations in year$_t$,

CFO_{t-1}, CFO_{t+1} - Are the previous and next period's cash flow from operations, respectively;

$\Delta FINT_t$ - Total financing changes in year$_t$, that includes changes in short-term and long-term bank financing, in shareholders loans, in equity and in others instruments of equity;

C_t - Dummy variable that takes the value 1 if $\Delta FINT_t > 0$, 0 otherwise;

ξ_t, μ_t - Estimation errors which complies the classical assumptions of the models estimated by Ordinary Least Squares.

After accruals models estimation for each version, we compute the ERR, as mentioned before, according to the difference between DAC_C and DAC_{NC} for each observation. To show the impact on DAC of the missing control for $\Delta FINT_t$, we performed a graphical and simulation analysis that, for ease of exposition, will be explained in detail in the results section.

In order to test for Shan et al. (2013) proposals, we also use the methodologies detailed in their paper, namely the matched-firm approach based on Kothari et al. (2005).

Sample dataset and descriptive statistics[6]

The basic sample is composed of all private Portuguese firms included in the Iberian Balance Sheet Analysis System (SABI) with data for the period 1998-2007. This period, in its upper limit year, is constrained by the economic crisis that affected the Portuguese Economy after 2008. Take more recent years would risk to mix in the analysis unwanted effects.

Given their accruals and business specificities, financial and public firms are eliminated from the initial sample. Observations with missing data, and outliers for WCA_t (1%+1%) by year and industry, are also eliminated.

[4] Change in revenues in JM; cash flows from operations of the years *t-1*, *t* e *t+1* in the DDM; these same cash flows and the change in revenues in MM.

[5] Observations with null $\Delta FINT_t$ were eliminated.

[6] All statistical analysis is performed using the Statistical Analysis System (SAS) software.

For the purpose of regressing accruals models cross-sectionally, industries with less than 30[7] yearly observations, and observations with null financing changes are eliminated. After all eliminations, the final sample has 48,041 observations.

The following table displays the descriptive statistics of the main variables. As shown in expression (6) and discussed above, $\Delta FINT_t$ seems to be a determinant of WCA_t, and both variables tend to have similar distribution as suggested by the values displayed in Table 1-Panel A.

Table 1

Descriptive statistics

	Mean	*STD*	*Q1*	*Median*	*Q3*
Panel A: Variables of the models					
WCA_t	0.060	0.176	-0.029	0.042	0.136
INV_t	0.001	0.001	0.000	0.000	0.001
ΔREV_t	0.095	0.532	-0.078	0.046	0.216
CFO_{t-1}	0.061	0.167	-0.013	0.062	0.138
CFO_t	0.065	0.163	-0.016	0.065	0.147
CFO_{t+1}	0.070	0.256	-0.010	0.069	0.153
$\Delta FINT_t$	0.043	0.186	-0.035	0.017	0.106
Panel B: DAC estimates not controlling for $\Delta FINT_t$					
JM	0.000	0.148	-0.071	-0.002	0.069
DDM	0.000	0.061	-0.032	-0.002	0.031
MM	0.000	0.058	-0.030	-0.001	0.030
Panel C: DAC estimates controlling for $\Delta FINT_t$					
JM	0.000	0.142	-0.068	-0.001	0.066
DDM	0.000	0.060	-0.032	-0.002	0.031
MM	0.000	0.058	-0.030	-0.001	0.030

Notes:

Variables definition: WCA_t - Working capital accruals in $year_t$ defined as changes in current assets less changes in current liabilities less changes in cash plus changes in current maturities of long-term debt (See expression (1)); INV_t – is the inverse of average total assets of $year_t$; ΔREV_t – Change in revenue in $year_t$; CFO_t - cash flows from operations in $year_t$, CFO_{t-1}, CFO_{t+1} - are the previous and next periods cash flow from operations, respectively; $\Delta FINT_t$ –Total financing changes in $year_t$, that includes changes in short-term and long-term bank financing, in shareholders loans, in equity and in others instruments of equity (e.g., Shan et al., 2013; Zhang, 2007); DAC – discretionary accruals; JM, DDM and MM as defined above. All variables are deflated by average total assets. The number of observations is 48,041.

By definition of a linear regression, the mean of controlled and not controlled DAC is equal to zero in all models. The values of the remaining distribution moments displayed are very similar for controlled and not controlled estimations, the major differences arising for JM. This model also shows descriptive statistics twice as high as other models.

Table 2 displays correlation coefficients. An emphasis is given to the (expected) positive and statistically significant correlation between WCA_t and $\Delta FINT_t$, and the negative one between $\Delta FINT_t$ and CFO_t.

Table 2

Correlation coefficients Pearson/Spearman

	WCA_t	INV_t	ΔREV_t	CFO_t	CFO_{t-1}	CFO_{t+1}	$\Delta FINT_t$	C_t
WCA_t	1	0.084	0.265	-0.278	0.006**	0.002**	0.263	0.229
INV_t	0.093	1	0.210	0.041	0.019	0.051	0.039	0.025
ΔREV_t	0.316	0.128	1	0.106	-0.054	0.069	0.052	0.031
CFO_t	-0.271	0.025	0.124	1	-0.038	-0.005**	-0.287	-0.258

[7] Other studies eliminated industries with less than 10 observations by year (e.g., Kothari et. al., 2005; Shan et al., 2013). The choice of a larger number (30) in the current study intended to permit a better and more precise estimation of discretionary accruals.

CFO_{t-1}	-0.002**	0.025	-0.066	0.024	1	0.045	0.002**	-0.003**
CFO_{t+1}	0.039	0.036	0.081	0.028	0.133	1	0.005**	0.005**
$\Delta FINT_t$	0.292	0.055	0.041	-0.353	-0.001**	0.020	1	0.623
C_t	0.249	0.038	0.029	-0.310	-0.002**	0.014	0.851	1

Notes:

Variables definition as per Table 1. ** Stands for correlation not statistically significant at less than 10. All other correlations are statistically significant at less than 1%. The upper diagonal shows Pearson correlation coefficients; the lower Spearman's.

Moreover, it deserves to be highlighted the small correlation between $\Delta FINT_t$ and ΔREV_t, the only explanatory variable in JM, meaning that ΔREV_t tends to be independent of $\Delta FINT_t$, meaning that the former is unable to reflect on WCA_t the impact of financing changes. The correlation between $\Delta FINT_t$ and CFO_t is somehow higher than the one discussed, and this evidence suggests that the DDM and MM models may fit a little better than JM in reflecting the impact of financing changes on accruals estimation. However, in general, the correlations displayed suggest that the accruals models tend not to control for the impact of such changes.

4. Results

Let us remind the two empirical objectives of the current study: to analyse empirically whether different accruals models [Jones, (1991); Dechow and Dichev, (2002); and McNichols, (2002)] reflect the impact of changes in corporate financing in a similar way; to test Shan et al. (2013) proposal in the specific economic and entrepreneurial context of the current study.

Accruals models and control for financing changes

The three accruals models are regressed in two different versions that differentiate by the control for the sign of $\Delta FINT_t$, included in the second version (C_t, a dummy variable that takes value 1 if $\Delta FINT_t$>0, 0 otherwise). Table 3 presents the accruals models estimation for each version.

Table 3

Estimated versions of accruals models not controlling (NC)/ controlling (C) for changes in financing

	Models	JM		DDM		MM	
	Exp. Sign	NC	C	NC	C	NC	C
		Coef. *(P-value)*	Coef. *(P-value)*	Coef. *(P-value)*	Coef. *(P-value)*	Coef. *(P-value)*	Coef. *(P-value)*
Intercept	?	0.048	0.002	0.080	0.041	0.072	0.038
		(0.000)	*(0.108)*	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
INV_t	?	6.287	5.391				
		(0.000)	*(0.000)*				
ΔREV_t	+	0.086	0.084			0.099	0.096
		(0.000)	*(0.000)*			*(0.000)*	*(0.000)*
C_t	+		0.079		0.060		0.054
			(0.000)		*(0.000)*		*(0.000)*
CFO_{t-1}	?			-0.004	-0.002	0.012	0.014
				(0.332)	*(0.647)*	*(0.005)*	*(0.001)*
CFO_t	-			-0.299	-0.252	-0.333	-0.290
				(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
CFO_{t+1}	?			0.001	0.000	-0.014	-0.014
				(0.805)	*(0.941)*	*(0.000)*	*(0.000)*
R^2		7.12%	11.99%	7.72%	10.38%	16.56%	18.68%
R^2 AJUST.		7.12%	11.98%	7.72%	10.37%	16.56%	18.67%

Models:

$$\text{JM}\begin{cases} NC \;\Rightarrow WCA_t = \alpha_0 + \beta_1 INV_t + \beta_2 \Delta REV_t + \xi_t \\ C \Rightarrow WCA_t = \alpha_0 + \beta_1 INV_t + \beta_2 \Delta REV_t + \theta_1 C_t + \mu_t \end{cases}$$

$$\text{DDM}\begin{cases} NC \;\Rightarrow WCA_t = \alpha_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \xi_t \\ C \Rightarrow WCA_t = \alpha_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \theta_1 C_t + \mu_t \end{cases}$$

$$\text{MM}\begin{cases} NC \;\Rightarrow WCA_t = \alpha_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \beta_4 \Delta REV_t + \xi_t \\ C \Rightarrow WCA_t = \alpha_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \beta_4 \Delta REV_t + \theta_1 C_t + \mu_t \end{cases}$$

Notes:
C_t - dummy variable that takes the value 1 if $\Delta FINT_t > 0$, 0 otherwise. The remaining variables defined as per Table 1. JM and MM do not include fixed assets as an independent variable because the dependent variable WCA_t does not include the depreciation and amortization component. The number of observations is 48,041. The models were regressed cross-sectionally by year and industry and the presented coefficients are averages.

All coefficients have the expected sign and are statistically significant. It is worthy to note that the C_t coefficient is significantly positive in all models. This means that $\Delta FINT_t$ has a positive impact in explaining WCA. For all models the incremental explanatory power of C_t is quite substantial, and the adjusted R^2 increases. For example, in the case of JM, from 7.12% (version NC) up to 11.98% (version C).

The impact on DAC estimates caused by the inclusion of C_t variable in accruals models is discussed next.

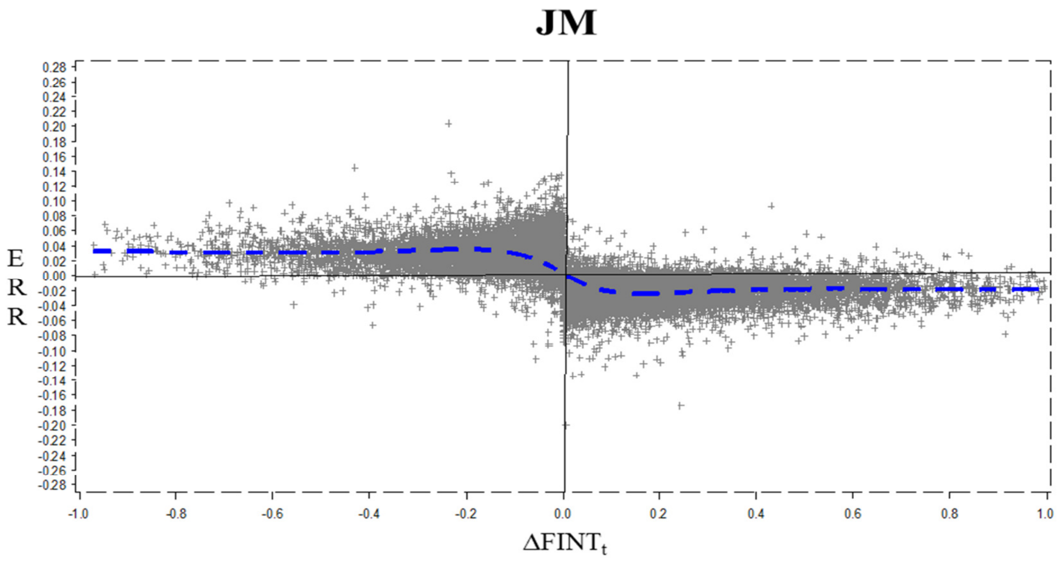
Graphical analysis

In section 2 it was anticipated that missing control for $\Delta FINT_t$ implies that DAC are overestimated for firm-years that recorded ΔPF (positive financing changes) and underestimated for those recording ΔNF (negative financing changes). In order to test these predictions graphical analyses are performed.

For each model, DAC measurement error (ERR) is plotted against the size of the correspondent $\Delta FINT_t$, and a dashed line is added to show the ERR average trend. The graphs are easy to read. For example, for JM a $\Delta FINT_t$ of 20% of total assets (0.2) implies an average ERR of about minus 3% of total assets (-0.03).[8]

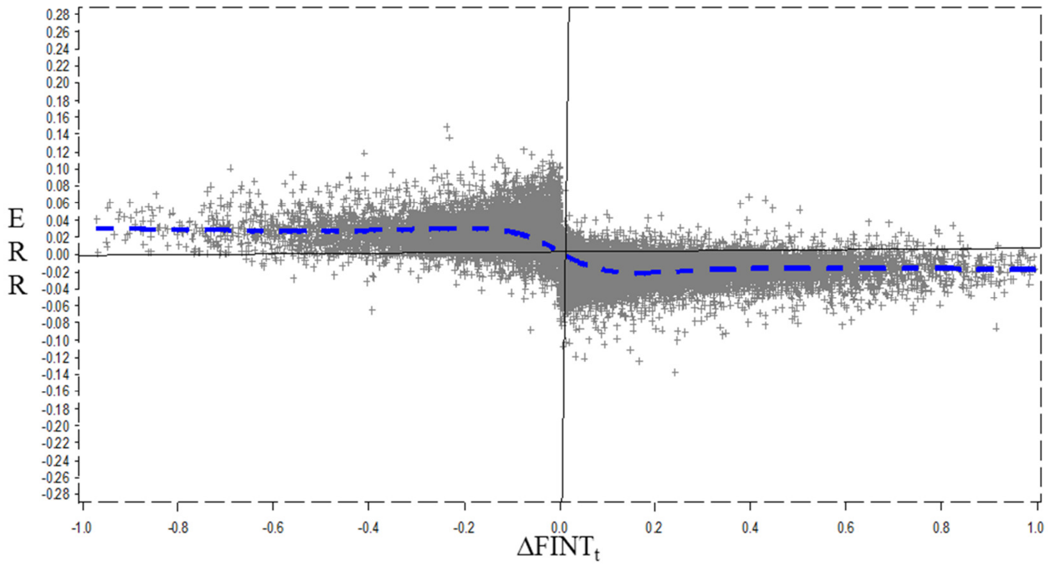
Graph 1

Difference between DAC_C and DAC_{NC} estimates (ERR) by size

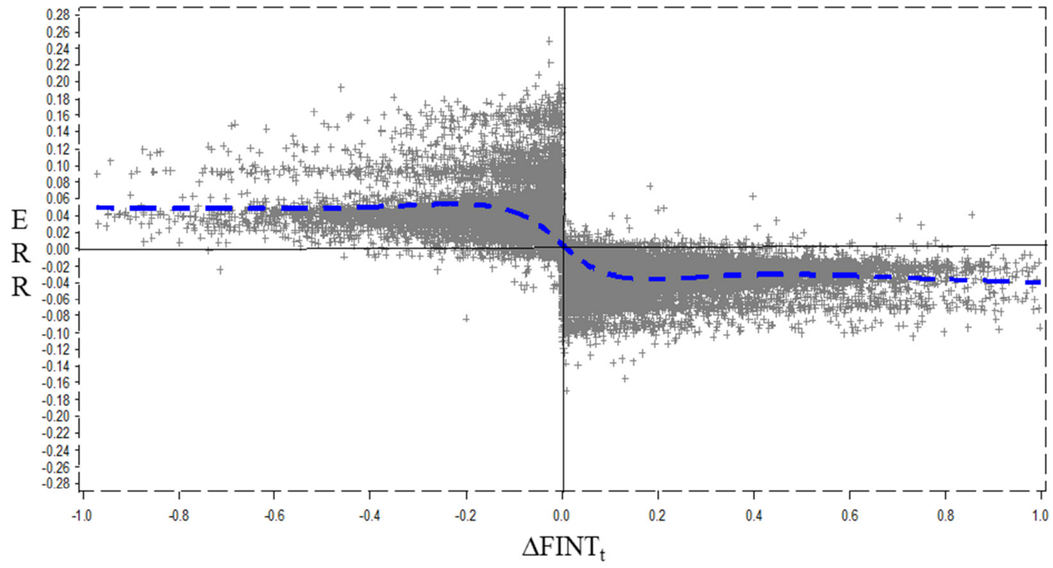


[8] DAC estimates are the residuals of the models regressed cross-sectionally by year and industry. 48,041 firm-years have been used. Industries are defined at a two-digit level of the Portuguese economic classification (V3).

DDM



MM



The graphical evidence corroborates the above discussed expectations. DAC do contain a measurement error due to model missing control for ΔFINT. Such an error (ERR = DAC_C - DAC_{NC}) is consistently negative for firm-years reporting ΔPF, meaning that in such cases DAC are overestimated; consistently positive for firm-years reporting ΔNF, meaning DAC are underestimated. All models tend to reflect in a similar way the control for the impact of financing changes. The dashed (trend) lines help to assess the similarity across models, and show that the means of measurement errors are almost similar for small and extreme financing changes. In this aspect, the empirical evidence in the current paper extends, and somehow contradicts, Shan et al. (2013) results, that suggest measurement errors occur mainly for extreme financing changes. In sum, the evidence shows that all models tend to have similar specification problems related to financing changes.

Simulation analysis

Now a simulation analysis is performed (e.g., Dechow et al., 1995; Hribar & Collins, 2002; Kothari et al., 2005; Shan et al., 2013). It is a complementary way of testing the quality of accruals models specification, testing whether ERR is statistically different from zero for a given ΔFINT. The aim is to test the robustness of the graphical results discussed above, by computing the probability to commit a Type I error when ERR = 0, i.e. to incorrectly reject the true null hypothesis, H0.

The first step begins by taking the basic sample of 48,041 observations and create 250 random samples with 1,000 observations. Each sample is extracted from the complete sample. This first set of 250 random samples is taken as the simulation set with 0% of contamination, i.e. a set where ERR, the core variable, is assumed to be zero. Based on this set of random samples, the rejection frequencies or Type I error rates are estimated, using a two[9] tailed t-test, for confidence levels of 1% and 5%.[10]

The second step adopts the same procedure described previously with a little difference: the random samples are contaminated with a given percentage of observations that must belong to a particular subset of the basic sample. As observed in the graphical analysis, for all models the trend line shows that the mean of estimation errors are almost similar for small and extreme financing changes. Thus, in order to test whether the results show a similar behaviour to that depicted in the graphical analysis, contamination is done using, firstly, observations with extreme positive and negative ΔFINT; secondly, observations with ΔFINT close to zero.[11] The contamination process starts with an "infection" rate of 10%, that consists in creating 250 intermediate random samples, without replacement[12], of 100 (1,000*10%) observations that belong to the subset of extreme (close to zero) observations; and 250 intermediate random samples, without replacement, of 900 (1,000*(100%-10%)) observations extracted from the whole basic sample. Merging both intermediate samples the output is a set of 250 random samples of 1,000 observations, with a 10% contamination level. The probability of committing Type I errors, and consequently the rejection percentages, can now be estimated as described above.

The results are displayed in Table 4. In Panel A it can be seen that for a contamination level of 0% two of the DAC models (JM and DDM) seem not well-specified, because they have rejection rates (2.0%)[13] above the level of confidence established (1%). In Panel B, and for the same level of contamination (0%), the rejection percentages increase slightly (8.8% up to 10.4%), and are now, for all models, above the defined level of confidence (5%). Thus, the rejection percentage of H0 is, generically in any of the accruals models, higher than the level of confidence adopted.

When the contamination degree increases up to 10% the percentages of rejection increase very significantly for all models, reaching in the case of MM 95.2% for the simulation sample infected with extreme negative financing changes ($\Delta FINT_t<0_{/<Q1}$). For DDM and JM the percentages of rejection are similar and higher than the adopted confidence level. For degrees of contamination up to 20%, for both 1% or 5% levels of confidence, the percentages of rejection goes up to 100%, whatever the nature ("close to zero" or "extreme") of the measurement errors.

The results are in line with the graphical analysis discussed above. As observed in the graphical analysis, the ERR seems to be almost similar, in all models. The percentages of rejection ERR=0 are also almost similar for small and extreme positive or negative financing changes. Thus, using this methodology the empirical evidence also suggests that the models under analysis are not well-specified when do not control for financing changes. There is a measurement error that is statistically different from zero. The percentages of rejection of H0 are, for all models and degrees of contamination, higher than the confidence levels adopted (1% or 5%).

[9] Because the hypothesis (H1) is considered in the alternative way, i.e. that ERR$\neq$ 0.
[10] The average ERR of each of the 250 samples is tested against the null hypothesis (H0), out of 250 tests (t-test) performed, which assumes that the per sample average ERR = 0. The rejection frequencies are the number of times H0 is rejected, divided by 250.
[11] The definition of the subsets of extreme and close to zero observations is as follows. Negative (positive) ΔFINT were split into quartiles. "Extreme observations" are those below the first quartile (above the third quartile); "close to zero" observations are those that lie above the third quartile (below the first quartile).
[12] Without replacement means that an observation appears once in each random sample with 1,000 observations.
[13] The percentage (2.0%) corresponds to the relative number of times, out of 250 tests (t-test) performed, the H0 hypothesis is rejected, i.e. to the number of times the ERR average by random sample is statistically different from zero.

Table 4

Percentages of rejection by degree of contamination

% of contamination	0%	10%				20%				30%			
		$\Delta FINT_t$<0		$\Delta FINT_t$>0		$\Delta FINT_t$<0		$\Delta FINT_t$>0		$\Delta FINT_t$<0		$\Delta FINT_t$>0	
		<Q1	>Q3	<Q1	>Q3	<Q1	>Q3	<Q1	>Q3	<Q1	>Q3	<Q1	>Q3
Panel A: 1% confidence level													
JM	2.0%	50.0%	80.0%	44.8%	51.2%	100.0%	100.0%	99.2%	99.2%	100.0%	100.0%	100.0%	100.0%
DDM	2.0%	80.4%	84.4%	60.4%	43.6%	100.0%	100.0%	99.6%	97.2%	100.0%	100.0%	100.0%	100.0%
MM	0.4%	78.8%	84.0%	82.8%	33.2%	100.0%	100.0%	100.0%	98.4%	100.0%	100.0%	100.0%	100.0%
Panel B: 5% confidence level													
JM	8.8%	75.2%	92.0%	70.0%	76.0%	100.0%	100.0%	99.6%	99.6%	100.0%	100.0%	100.0%	100.0%
DDM	10.4%	93.6%	96.4%	86.0%	70.4%	100.0%	100.0%	100.0%	98.8%	100.0%	100.0%	100.0%	100.0%
MM	9.6%	95.2%	94.8%	94.4%	61.6%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Notes:
This table displays the percentages of rejection by degree of contamination. The percentages of rejection correspond to the relative number of times, out of 250 tests (t-test) performed, the H0 hypothesis is rejected, i.e., the number of times the ERR average by random sample is statistically different from zero. The mentioned quartiles are defined independently for negative (positive) ΔFINT. For levels of contamination exceeding 40% the percentage of rejection is always 100%. The confidence level is used to establish if H0 hypothesis is rejected or not.

Testing Shan et al. (2013) methodology

As proposed in the Introduction, Shan et al. (2013) methodology was taken and tested in the Portuguese context. Once again, the purpose of the experiment was to show the existence of measurement errors in discretionary accruals due to the lack of control for the financial changes. The additional empirical evidence shows results quite similar to those obtained in accordance with our methodology, corroborating that DAC contains a measurement error or bias when no control for financing changes is undertaken.

According to Shan et al. (2013), using the matched-firm approach on financial changes, based on Kothari et al. (2005), the measurement errors in discretionary accruals are eradicated. However, this not occurs in the Portuguese context. The results seem to be driven by the economic and entrepreneurial context of the analysis[14]. In summary, the evidence shows that the measurement error in discretionary accruals estimates, caused by ΔFINT, is not completely controlled by the discussed methodologies. The economic and entrepreneurial context seems to play an active role in their inability to accomplish such a control.

5. Summary

The aim of the present study was to analyse the specification of accruals models under financing changes. It pursues to show analytically how the occurrence of such changes affects discretionary accruals estimation, to analyse whether different accruals models reflect in a similar way the impact of financing changes and compare for the Portuguese context the efficiency of the proposed methodology to Shan et al. (2013), in order to assess the relative performance of each one. Three models have been tested empirically: JM, DDM and MM.

Using a methodology based on a comparative static approach, with graphical and simulation analyses, the results supported the expectations: when there are financing changes the accruals models are not well-specified, suffering from an omitted variables bias. Moreover, the analyses showed that the measurement error in accruals estimates depends on the sign of these changes, and occurs regardless of financing changes size.

Beyond our own methodology, we tested also a solution available in the literature, Shan et al.(2013), but like ours it is not completely effective in the context underlying the current study.

The current study makes three main contributions. Firstly, it adds to the available literature and shows that there is a measurement error in accruals estimates arising from accruals models that do not control for financing changes, and their positive/negative sign. Secondly, it also shows that the estimation errors occur regardless of the size and sign of financing changes. Thirdly, it brings news insights on the estimation of accruals in a context of non listed small and medium firms.

The current study must be seen as just another step towards a better understanding of accruals models and their limitations. Future research can improve it by extending the analysis to other accruals models, and propose different and complementary research methodologies to cope with the misspecification of accruals models.

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[14]For the sake of parsimony, and because no extra information would be conveyed to the paper, the results are not tabulated. They are available from the authors on request.

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