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Accruals, Investment and Errors-in-Variables*

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Résumé

Dans cet article, nous reformulons les modèles classiques d'accruals dans le cadre de la théorie de l'investissement. Étant donné que les accruals sont assimilables à des investissements à court terme, nous incorporons i) les cash-flows comme proxy des contraintes financières et autres imperfections de marché, et ii) le *q* de Tobin comme mesure du rendement du capital. Puisque les données comptables, tels que les cash-flows, et le *q* de Tobin sont mesurés avec erreur, nous proposons une nouvelle méthode économétrique basée sur une version modifiée de la régression artificielle d'Hausman qui recourt à une matrice optimale pour pondérer les estimateurs à moments supérieurs de manière à obtenir des instruments robustes. Les résultats empiriques suggèrent que tous les paramètres-clefs des modèles d'accruals discrétionnaires étudiés sont systématiquement biaisés en raison de la présence d'erreurs de mesure.

Mots-clefs: Accruals discrétionnaires; Manipulation des états financiers; Investissement; Erreurs de mesure; Moments supérieurs; Estimateurs à variables instrumentales.
***Classification JEL*:** M41; C12; D92.

Abstract

In this paper, we formulate well-known discretionary accruals models in an investment setting. Given that accruals basically consist of short-term investment, we introduce, (i) cash-flows, as a proxy for financial constraints and other financial markets imperfections, and (ii) Tobin's *q* as a measure of capital return. Accounting data, as cash-flows, and Tobin's *q* being measured with errors, we propose an econometric method based on a modified version of the Hausman artificial regression which features an optimal weighting matrix of higher moments instrumental variable estimators. The empirical results suggest that all the key parameters of the discretionary accruals models studied are biased systematically with measurement errors.

Keywords: Discretionary accruals; Earnings management; Investment; Measurement errors; Higher moments; Instrumental variable estimators.
***JEL classification*:** M41; C12; D92.

1. Introduction

In a strict accounting framework, accruals are defined as the difference between earnings and cash-flows (Jones, 1991; Bartov et al., 2001). Discretionary accruals models are used by practitioners to assess the level of non-discretionary accruals, an important indicator providing information on the nature of firms earnings, and a significant predictor of stocks returns (Fama and French 2007, Hirshleifer and al. 2009). Despite the fact that accruals carry valuable information for investors, the standard models used so far to estimate non-discretionary accruals (e.g., Jones 1991, Bartov et al 2001, Xie 2001, Kothari et al. 2005, Wu et al. 2007) rarely go beyond OLS estimation. However sophisticated, and even if some models might take into account various aspects of simultaneity bias, many do not directly address the problem of errors-in-variables. Noticeable exceptions include Kang and Sivaramakrishnan (1995), Hansen (1999), Young (1999), Hribar and Collins (2002), Zhang (2007), and Ibrahim (2009). However, the treatment of errors-in-variables they propose is incomplete in the sense that it should be complemented with an econometric approach. This is the primary aim of this paper.

We revisit the estimation of aggregate discretionary accruals using a new method to account for measurement errors[1]. We apply this method to the estimation of two commonly used discretionary accruals models, (i) the Jones (1991) model, considered as a benchmark, and (ii) the augmented Jones model including cash-flows (Dechow 1994, Zhang 2007). Another important contribution of this paper is the introduction of a third type of accruals model, where accruals are specified as short-term investment. For this third model, we adopt Zhang (2007) investment perspective on accruals. As he notes, “Surprisingly, little is known

[1] On previous applications of this method see Coën and Racicot (2007) and Racicot and Théoret (2009).

in the literature about the investment perspective of accruals despite the fact that, by definition, accruals measure investment in working capital" (p.6). Following Zhang (2007), we thus introduce cash-flows in the Jones (1991) accruals model. The standard formula of accruals misses key aspects of accruals, namely the fact that accruals constitute a form of short-term investment, at least in terms of working capital. A noticeable exception is the model of Dechow (1994), which introduces cash-flows as a regressor. To deal with the simultaneity bias created by the colinearity between accruals and cash-flows, the author considers lagged cash-flows. While this procedure might be adequate to mitigate the autocorrelation of the error term, it does not deal explicitely with the endogeneity issue (Theil 1953). Note that, in this third version of the accruals model, cash-flows are no longer viewed as a performance measure as in Dechow (1994), but as a proxy for financial constraints, as generally assumed in the investment literature. Given the investment flavour of our third accruals model, we include Tobin's *q* as an additional regressor in the equation. However, the inclusion of Tobin's *q* also adds to the endogeneity problem, this variable being measured with error, a well documented fact in the investment literature (e.g., Hayashi 1982, Erickson and Withed 2000 and 2002).

Usually, the basic Jones model and its variants are estimated using OLS. Sometimes the accruals models account for heteroskedasticity, with a form of weighted least-squares. But the measurements errors inherent to accounting data are often ignored. This may cause a serious bias in the estimation, because the orthogonality between the explanatory variables and the equation innovation is not necessarily satisfied. Furthermore, most studies on accruals are based on *ad hoc* models which resort to arbitrary variables to explain accruals, instead of a choice based on sound theoretical foundations.

We aim at examining non-discretionary and discretionary accruals – the latter being the error term of the accruals models – bearing in mind the fact that this error term is the portion of accruals managed by the entrepreneurs. According to Dechow et al. (1995), Beneish (1997), Burghstahler and Dichev (1997), Jeter and Shivakumar (1999), Peltier-Rivest and Swirsky (2000), Peasnell et al. (2000), Xie (2001), Marquardt and Wiedman (2004), Hirshleifer et al. (2004), Garcia et al. (2005) and Barua et al. (2006), firms managers may sometimes falsify discretionary accruals, and this may result in a statistical anomaly worth detecting. Indeed, since discretionary accruals are often used to forecast market returns, it is therefore important to resort to a *robust* estimation method in order to compute these accruals with the greatest possible precision (Ibrahim 2009). It is well understood by econometricians that ignoring measurement errors leads to the underestimation or overestimation of relevant parameters. The most dramatic implication of this omission is the bias resulting from the correlation of the error term with the vector of regressors.

In this paper, we propose econometric techniques to specifically address the issue of errors-in-variables in discretionary accruals models. The instruments used are based on a weighted optimal matrix of the higher moments and cumulants of the explanatory variables (Racicot and Théoret 2009). We apply these optimal instruments in the classical GMM estimation to obtain a new estimator, the GMM-C, and run an endogeneity test based on the Hausman artificial regression (named the Haus-C). In this respect, our contribution is to adapt this procedure to pooled data of discretionary accruals.

In other respect, the definition of accruals includes cash-flows despite the fact that it is an explanatory variable in our accruals model, i.e. this is a clear endogeneity issue. To control for this, we replace the cash-flows variable by its predicted value, which is orthogonal to the error term. A naïve approach often found in the accounting literature is to lag cash-flow to correct for this common endogeneity issue. While this procedure might be adequate to mitigate the error term autocorrelation, it is rather inappropriate to tackle endogeneity (Theil 1953). Our results about cash-flows tend to corroborate the view according to which there are important market imperfections impending the Modigliani and Miller result to hold in the short run (Brown and Petersen 2009, Brown et al. 2009). In the context of our models, these imperfections might also be associated to liquidity constraints, and the preference to directly self-finance accruals with cash-flows before resorting to external finance (Gilchrist and Himmelberg 1995, Bates et al. 2009)[2].

Our results suggest that measurement errors have a great influence on the parameters estimation of the basic ad hoc Jones accruals model. More precisely, our estimation of the Jones model reveals that important measurements errors contaminate the accounting measures of sales and fixed assets. The results concerning the new model of accruals we introduce, based on investment theory setting, are particularly interesting. First, Tobin's *q*, which, as the theory predicts, has already a very significant positive impact on non-discretionary accruals when using the OLS method, displays an increased explanatory power when applying the new Haus-C procedure. According to the theory, it is the marginal and not the average Tobin's *q* which influences investment. As marginal Tobin's *q* – the discounted expected value of all marginal cash-flows of one unit of capital over its lifetime, i.e. the shadow price of capital divided by its cost – is unobservable, researchers often resort to average Tobin's *q* as a proxy. Our results confirm that this procedure is questionable. Indeed, this key variable seems to be plagued by serious measurement errors. Relatedly, the Haus-C procedure delivers a coefficient of the error adjustment regressor comparable in level to the

[2] The fact that firms prefer self-financing over external funding is related to the pecking order theory.

Tobin's q coefficient itself. As a matter of fact, we can interpret Tobin's q measurement error as further evidence that firms expectations are partly incorporated in future cash-flows, a point often mentioned in the empirical literature on investment. In this respect, when introducing Tobin's q in the accruals equation corrected for measurement errors, we find that the cash-flow variable has a smaller influence on short term investment. In other words, when measurement errors are properly accounted for, the traditional role of Tobin's q is reinforced, while financial constraints seem to play a minor role, although non trivial.

This paper is organized as follows. In section 2, we present our accruals models to be estimated with pooled data and our methodology to address the problem of endogeneity and errors-in-variables in the accruals models. In section 3, we detail the empirical results. Section 4 concludes.

2. Method

2.1 The Models

Total accruals are generally defined as follows

$$\text{Accruals} = \text{Earnings} - \text{Cash-flows} \qquad (1)$$

Accruals may also be expressed in terms of investment. More precisely, accruals may be defined as

$$TA \equiv \left(\Delta CA - \Delta CASH\right) - \left(\Delta CL - \Delta STD - \Delta TP\right) - DEP \qquad (2)$$

where ΔCA stands for change in current assets; $\Delta CASH$, change in cash or cash equivalents; ΔCL, change in current liabilities; ΔSTD, change in debt included in current liabilities; ΔTP, change in income taxes payable; DEP, depreciation and amortization expenses.

Since we want to focus on the short-term component of investment, i.e. the working capital component of accruals, we propose an alternative definition which eliminates the long term element of equation (2), i.e. total depreciation, that is

$$TA \equiv (\Delta CA - \Delta CASH) - (\Delta CL - \Delta STD - \Delta TP) \qquad (3)$$

with

$$TA_t = \hat{TA}_t + \varepsilon_t \qquad (4)$$

where $\hat{TA}_t$ represents the estimated non-discretionary accruals, and ε_t the discretionary accruals.

2.1.1 The Jones Model of Accruals

The Jones (1991) model of accruals, considered as a benchmark in the literature, can be written as:

$$\frac{TA_{it}}{A_{i,t-1}} = \alpha_s\left(\frac{1}{A_{i,t-1}}\right) + \beta_s\left(\frac{PPE_{it}}{A_{i,t-1}}\right) + \delta_s\left(\frac{\Delta REV_{it}}{A_{i,t-1}}\right) + \varepsilon_{it} \qquad (5)$$

where *TA* is total accruals; *A*, total assets; *PPE*, gross property plant and equipment at the end of year *t*; *ΔREV*, revenues in year *t* less revenues in year *(t-1)*. Note that all variables in this model are scaled by $A_{i,t-1}$ to account for heteroskedasticity. This precaution also helps control for size effects.

The equation may be decomposed in two parts: the non-discretionary accruals and the discretionary accruals. The fitted value of the equation, $\frac{\hat{TA}_{it}}{A_{i,t-1}}$, represents the non- discretionary accruals, while the innovation, ε_{it}, is the discretionary part of accruals.

There are two control variables in the Jones model. The variable ΔREV_{it}, replaced by the change in sales in the literature (Cormier et al. 2000), controls for the economic environment of the firm, and measures firms operations before manager manipulations. In many studies, the estimated coefficient of this variable is found positive. However according to McNichols and Wilson (1988), the expected sign is actually ambiguous because a given change in revenues may cause positive/negative changes in the components of accruals. For this reason, these authors advocate the use of a specific model for every component of non-discretionary accruals. In other respect, to minimize income taxes, some managers might voluntarily underestimate reported revenues. For instance, managers can shift fraudulently to the following year merchandise deliveries during import relief investigation years (Jones 1991). Hence, ΔRev may be contaminated by measurement errors.

Second, the PPE_{it} variable controls for the part of total accruals which actually relates to the (non-discretionary) depreciation expenditures. As part of total accruals, this control variable might be colinear to total accruals. Consequently, this variable often presents a standard endogeneity issue. However, some authors (e.g. Kaplan, 1979) still support this choice of variable and ignore the endogeneity issue. As a depreciation expense, we expect a negative sign of the PPE_{it} coefficient because this variable measures a cash-flow reducing accruals. This rationale is based on an accounting argument but is also consistent with investment theory, *PPE* being a proxy for depreciation. Indeed, investment is equal to $I_t = K_t - (1-\delta)K_{t-1}$, where δ stands for the rate of depreciation. The PPE_{it} variable is a substitute for δ and stands for the long term component of investment. Hence, its expected sign is negative, with an increase in δ resulting in a decrease in investment.

Since this study focuses on short-term investment, measured by working capital, we omit PPE_{it}, a long term investment component, in our revised version of the model. Equation (6) obtains:

$$\frac{TA_{it}}{A_{i,t-1}} = \alpha_s\left(\frac{1}{A_{i,t-1}}\right) + \delta_s\left(\frac{\Delta REV_{it}}{A_{i,t-1}}\right) + \varepsilon_{it} \qquad (6)$$

Note that the same procedure is followed for every model. First, we analyze the long-term version, with *DEP* and *PPE* included in the models. Second, we estimate a short-term version without *PPE* and *DEP*, its corresponding counterpart in the accruals variable.

2.1.2 An Augmented Version of the Jones Model with Cash- Flows

To account for firm performance, Dechow (1994) introduces cash-flows (*CF*) in the Jones model. In its long term form, the augmented accruals model may be written as:

$$\frac{TA_{it}}{A_{i,t-1}} = \alpha_s\left(\frac{1}{A_{i,t-1}}\right) + \beta_s\left(\frac{PPE_{it}}{A_{i,t-1}}\right) + \delta_s\left(\frac{\Delta REV_{it}}{A_{i,t-1}}\right) + \kappa_s\left(\frac{CF}{A_{i,t-1}}\right) + \varepsilon_{it} \qquad (7)$$

The corresponding short-term version of equation (7) is:

$$\frac{TA_{it}}{A_{i,t-1}} = \alpha_s\left(\frac{1}{A_{i,t-1}}\right) + \delta_s\left(\frac{\Delta REV_{it}}{A_{i,t-1}}\right) + \kappa_s\left(\frac{CF}{A_{i,t-1}}\right) + \varepsilon_{it} \qquad (8)$$

In the context of our study, we consider the introduction of the cash-flow variable in equation (7) as a first step in casting the accounting accruals model in an investment perspective. Since accruals can be viewed as short term investments, cash-flow might be a key explanatory variable of the model. In corporate finance, cash-flows are generally introduced as a proxy for firm liquidity constraints. If financial markets were perfect, firm cash-flows should not have a significant impact on investment. Indeed, in this case, economic theory predicts that investment is only dependent on the marginal Tobin's q. But if financial markets are assumed imperfect, firm financial structure might no longer be neutral, and liquidity constraints then have a significant impact on investment. In this case, a decrease in cash flows could lead to a decrease in investment if the firm is financially constrained or in the presence of credit rationing[3]. The significant cash-flows investment sensitivity often found in the literature (e.g. Brown and Petersen 2009) also relates to financial markets incompleteness. In a dynamic framework, the self-enforcing contract theory (c.f.. Hart and Holmström 1987, Marcet and Marimon 1992, Thomas and Worrall 1994, Albuquerque and Hopenhayn 2004) suggests another interpretation for the presence of cash-flows as a significant explanatory variable in investment equations. When a firm is under financial stress, that is when its cash-flows are low, it can display a tendency to overinvest in order to generate future cash-flows in order to relax its expected financial constraint. In this case theory predicts a negative relationship between cash-flows and investment (Calmès 2004).

2.1.3 The Tobin's q Augmented Accruals Model

We also introduce Tobin's q as an additional explanatory variable in the equation of long term accruals:

$$\frac{TA_{it}}{A_{i,t-1}} = \beta_1\left(\frac{1}{A_{i,t-1}}\right) + \beta_2\frac{PPE_{it}}{A_{i,t-1}} + \beta_3\frac{\Delta Sales_{it}}{A_{i,t-1}} + \beta_4\frac{q_{it(or\, i,t-1)}}{A_{i,t-1}} + \beta_5\frac{CF}{A_{i,t-1}} + \xi_{it} \quad (9)$$

[3] Note that this explanation is related to an intra-temporal model of investment, that is a static model (as opposed to an intertemporal or dynamic setting). In the same vein, there is also a static approach based on the theory of asymmetric information and agency theory. In this theory, the dynamics of investment is completely absent, and with the asymmetric setting, the classical positive link between cash-flows and investment obtains. A firm whose financial constraint is binding has no other choice but to reduce investment, because of the prohibitive borrowing cost it faces.

where Tobin's q, the shadow price of capital, is proxied by[4]

$$\frac{Market\ value\ of\ capital + Accounting\ value\ of\ debts}{Accounting\ value\ of\ assets} \tag{10}$$

As done for the previous models, we analyse the short-term version of equation (9):

$$\frac{TA_{it}}{A_{i,t-1}} = \beta_1\left(\frac{1}{A_{i,t-1}}\right) + \beta_3\frac{\Delta Sales_{it}}{A_{i,t-1}} + \beta_4\frac{q_{it(or\ i,t-1)}}{A_{i,t-1}} + \beta_5\frac{CF}{A_{i,t-1}} + \xi_{it} \tag{11}$$

Instead of using *ROA* as the yield variable as done in Kothari et al. (2005), we rely on Tobin's q as our yield measure, which additionally provides an investment perspective on accruals. The yield of investment is a key variable of the accruals model, because, as economic theory predicts, investment is only related to its yield (especially if markets are perfect). Furthermore, not having this variable in the accruals model tends to melt the yield and the liquidity constraint (cash-flows) proxying financial markets imperfections. More precisely, the classical theory predicts that investment depends only on its yield (according to the famous Modigliani and Miller theorems). In theory, investment is optimal when the rental rate is equal to the marginal product of capital. In other words, at equilibrium, the marginal cost of capital must be equal to its marginal revenue. But these theorems assume perfect markets. If markets are actually imperfect, the cash-flow variable becomes a potential significant regressor, as financial constraints tend to influence both the capital structure and the performance of the firm.

[4] Since we work in an accounting framework, we thus rely on an accounting definition of Tobin's q. Incidentally, there are many empirical measures for Tobin's q. One popular measure used in economic studies defines Tobin's q as the ratio of the market value of assets to their replacement cost. This measure is used to study firm performance. However, regardless the way it is proxied for, it is well-known fact that Tobin's q remains measured with errors. There are many ways to account for these errors. For instance, Baele et al. (2007) use a noise-adjusted Tobin's q to study banks performance. In our study, we use instruments to correct Tobin's q for measurement errors, a standard procedure in econometrics.

Consequently, we have to take into account the *forecasted cash-flows* in the dynamics of investment. There is much controversy regarding the measurement of Tobin's q, measurement errors creating a spurious interaction between Tobin's q and cash-flows. Theoretically, Tobin's q is a marginal concept but its observed empirical counterpart is an average one, the marginal measure being unobservable. Therefore, when using the average measure, cash-flows might embed information about Tobin's q, such that cash-flows and Tobin's q tend to be colinear. Thus, the relation between cash-flows and investment can be spurious in this case, unless we account for the resulting endogeneity of these variables. This matter is dealt with in the following section, where we present a modified Hausman artificial regression.

2.2 The Augmented Hausman Artificial Regression Based on Cumulants

2.2.1 Instruments

To deal with specification errors, Geary (1942), Durbin (1954), Kendall and Stewart (1963), Pal (1980), Fuller (1987), and more recently Dagenais and Dagenais (1997) and Lewbel (1997), have proposed instruments based on higher moments and cumulants. Racicot and Théoret (2009) have also generalized these instruments and applied them to financial models of returns testing and correcting specification errors in a GMM framework. As a matter of fact, the literature on financial risk relies increasingly on the cumulants as more reliable measures of risk (Malevergne and Sornette 2005).

The set of new instruments we propose to build an estimator accounting for specification errors (and more specifically errors in variables) is based on an *optimal* combination of the estimators of Durbin (1954) and Pal (1980). To the best of our knowledge, this kind of procedure has never been used for studying accruals so far.

To implement the Haus-C procedure, let us first assume the following general form $\mathrm{Y} = \alpha + \mathrm{X}\beta$, where **Y** is the vector (*n x 1*) representing the dependent variables and **X** is the matrix (*n x k*) of the explanatory variables. Assume further the existence of specification errors in the explanatory variables which might create inconsistency in the estimation of the vector β. To tackle this issue, Durbin (1954) proposes to use as instruments the following product: $x*x$, where x is the **X** matrix of the explanatory variables expressed in deviation from the mean and where the symbol * stands for the Hadamard element by element matrix multiplication operator. In the same vein, Pal (1980) introduces as instruments cumulants based on the third power of x instead of the squares, as Durbin. Combining these instruments, we obtain a new matrix of instruments **Z** based on the cumulants and co-cumulants of **x** and **y**, these being the matrix **X** and the vector **Y** expressed in deviation from the mean. This **Z** matrix may be partitioned into k vectors or series, i.e. $\mathbf{Z} = \begin{bmatrix} z_1 & z_2 & \dots & z_k \end{bmatrix}$. The vector z_1, which is built with the first explanatory variable, is the instrument of the first explanatory variable, and so on. We regress this vector **Z** on the explanatory variables to obtain $\hat{x}$

$$\hat{\mathbf{x}} = \mathbf{Z}(\mathbf{Z'Z})^{-1}\mathbf{Z'x} \qquad (12)$$

Then the new optimal instruments $\hat{\mathbf{w}}^{\mathbf{c}}$ based on cumulants of the explanatory variables are defined as:

$$\hat{\mathbf{w}}^{\mathbf{c}} = \mathbf{x} - \hat{\mathbf{x}} = [\hat{w}_1^c \quad \hat{w}_2^c \quad \dots \quad \hat{w}_k^c] \qquad (13)$$

In their study, Racicot and Théoret (2009) find that these instruments are orthogonal to their estimated residuals. In their study, the correlation between $\hat{w}_i^c$ and the corresponding explanatory variable x_i is around 90%, and the correlation is near 0 with the other explanatory variables. In this sense, these instruments can be considered optimal. To improve the existing instrumental methods used to tackle the endogeneity issue in accruals models, we thus adopt the $\hat{w}_i^c$ instruments they developed with a modified version of the Hausman (1978) artificial regression.

Of course, our starting point is that accruals models generally present specification errors. These errors might be due to many causes (Spencer and Berk 1981) like the omission of relevant variables, the aggregation level of the data, the accounting errors or simply an incorrect functional form. In any case, these errors may cause some explanatory variables to be endogenous. Consequently, the condition of orthogonality between these variables and the innovation term of the accruals models is violated: the estimators of the coefficients of the models are no longer unbiased nor consistent. To reduce the estimation biases related to these coefficients, we thus regress, in a first pass, the endogenous explanatory variables on instrumental ones. Then, the delicate part is to judiciously choose the instruments. This is where the optimal instruments prove to be particularly convenient.

2.2.2 The Augmented Hausman Artificial Regression

To detect specification errors in our sample of firms, we could use the original Hausman *h* test[5] with the following classical linear regression model: $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, where $\mathbf{Y}$ is a $(n \times 1)$ vector representing the dependent variable; $\mathbf{X}$, a $(n \times k)$ matrix of the explanatory variables; $\boldsymbol{\beta}$, a $(k \times 1)$ parameters vector, and $\boldsymbol{\varepsilon} \sim iid\ (0, \sigma^2)$. The Hausman test compares two estimates of the parameters vector, $\boldsymbol{\beta}_{\mathbf{OLS}}$, the least-squares estimator (OLS), and $\boldsymbol{\beta}_{\mathbf{A}}$, an alternative estimator taking a variety of specifications, but, for our purpose, is the instrumental variables estimator $\boldsymbol{\beta}_{\mathbf{IV}}$. The hypothesis H_0 is the absence of specification errors, and H_1, their

[5] For details on the Hausman test, see : Hausman (1978), Wu (1973), MacKinnon (1992) and Pindyck and Rubinfeld (1998). A very good presentation of the version of the Hausman test using an artificial regression in the context of correction of errors in variables may be found in Pindyck and Rubinfeld (1998). They present the case of one explanatory variable, whereas we apply it to the case of multiple explanatory variables.

presence. First note that the vector of estimates $\boldsymbol{\beta}_{\mathbf{IV}}$ is consistent under both H_0 and H_1, whereas $\boldsymbol{\beta}_{\mathbf{OLS}}$ is only consistent under H_0 and not consistent under H_1. Consequently, under H_0, $\boldsymbol{\beta}_{\mathbf{IV}}$ is less efficient than $\boldsymbol{\beta}_{\mathbf{OLS}}$.

Second, the Hausman test aims at verifying if "the endogeneity" of some variables, in our case the variables measured with errors, has any significant effect on the estimation of the parameters vector. Therefore, the Hausman test is an *orthogonality* test, that is, helping verify if *plim (1/T)* X'ε = 0 in large samples. To implement the test, we define the following vector of contrasts or distances: $\boldsymbol{\beta}_{\mathbf{IV}} - \boldsymbol{\beta}_{\mathbf{OLS}}$. The resulting *h* test statistic reads: $h = \left(\hat{\boldsymbol{\beta}}_{\mathbf{IV}} - \hat{\boldsymbol{\beta}}_{\mathbf{OLS}}\right)^T \left[\mathbf{Var}\left(\hat{\boldsymbol{\beta}}_{\mathbf{IV}}\right) - \mathbf{Var}\left(\hat{\boldsymbol{\beta}}_{\mathbf{OLS}}\right)\right]^{-1} \left(\hat{\boldsymbol{\beta}}_{\mathbf{IV}} - \hat{\boldsymbol{\beta}}_{\mathbf{OLS}}\right) \sim \chi^2(g)$, with $\mathbf{Var}\left(\hat{\boldsymbol{\beta}}_{\mathbf{IV}}\right)$ and $\mathbf{Var}\left(\hat{\boldsymbol{\beta}}_{\mathbf{OLS}}\right)$ the respective estimates of the covariance matrices of $\hat{\boldsymbol{\beta}}_{\mathbf{IV}}$ and $\hat{\boldsymbol{\beta}}_{\mathbf{OLS}}$, and *g* the number of potentially endogenous regressors. H_0 is rejected if the p-value of this test is less than *α*, the critical threshold of the test (e.g. 5%).

Third, and more importantly, note that, according to MacKinnon (1992), the *h* test might also run into difficulties if the matrix $[\mathbf{Var}\left(\hat{\boldsymbol{\beta}}_{\mathbf{IV}}\right) - \mathbf{Var}\left(\hat{\boldsymbol{\beta}}_{\mathbf{OLS}}\right)]$, which weights the vector of contrasts, is not positive definite. Since this is the case with most of the accruals models we study, we rely instead on an alternative method to run our Hausman test. For example, assume a five-variable linear regression model, the version of the accruals model incorporating Tobin's *q*:

$$y_t = \beta_0 + \sum_{i=1}^{5} \beta_i x_{it}^* + \varepsilon_t \qquad (14)$$

with $\varepsilon \sim iid\left(0, \sigma^2\right)$.

and that the variables x_{it}^{*} [6] are measured with errors, that is:

$$x_{it} = x_{it}^{*} + \upsilon_{it} \qquad (15)$$

with x_{it} the corresponding observed variables measured with errors. By substituting equation (15) in equation (14), we have:

$$y_t = \beta_0 + \sum_{i=1}^{5} \beta_i x_{it} + \varepsilon_t^{*} \qquad (16)$$

with $\varepsilon_t^{*} = \varepsilon_t - \sum_{i=1}^{5} \beta_i \upsilon_{it}$. As explained before, estimating the coefficients of equation (16) by the OLS method leads to biased and inconsistent coefficients because the explanatory variables are correlated with the innovation. Consistent estimators can be found if we can identify an instrument vector $\mathbf{z_t}$ which is correlated with every explanatory variable but not with the innovation of equation (16). Then we regress the five explanatory variables on $\mathbf{z_t}$. We have:

$$x_{it} = \hat{x}_{it} + \hat{w}_{it} = \hat{\gamma}_i \mathbf{z_t} + \hat{w}_{it} \qquad (17)$$

where $\hat{x}_{it}$ is the value of x_{it} estimated with the vector of instruments, and $\hat{w}_{it}$ the residuals of the regression of x_{it} on $\hat{x}_{it}$. Substituting equation (17) into equation (16), the following artificial regression obtains:

$$y_t = \beta_0 + \sum_{i=1}^{5} \beta_i \hat{x}_{it} + \sum_{i=1}^{5} \beta_i \hat{w}_{it} + \varepsilon_t^{*} \qquad (18)$$

The explanatory variables of this equation are, on the one hand, the estimated values of x_{it}, obtained by regressing the five variables on the vector of instruments $\mathbf{z_t}$, and on the other hand, the respective residuals of these regressions. Therefore equation (18) is an augmented version of equation (16).

[6] As usually done in econometrics, we use the asterisks to designate the unobserved variables.

We can show that:

$$p\lim\left[\frac{\sum \hat{w}_{it}\varepsilon_t^*}{N}\right] = p\lim\left[\frac{-\beta_1\sum x_{it}\upsilon_{it}}{N}\right] = -\beta_i\sigma_{\upsilon i}^2 \qquad (19)$$

If there is no specification error, $\sigma_{\upsilon i}^2 = 0$, the OLS estimation results in a consistent estimator for β_i, the parameter of $\hat{w}_{it}$ in equation (18), and the coefficient is then equal to the one of the corresponding explanatory variable. In the case of specification errors, $\sigma_{\upsilon_i}^2 \neq 0$ and therefore the estimator is not consistent.

For detecting the presence of specification errors, as we do not know a priori if there are such errors, we first have to replace the coefficients of the $\hat{w}_{it}$ in equation (18) by θ_i. We thus have:

$$y_t = \beta_0 + \sum_{i=1}^{5} \beta_i\hat{x}_{it} + \sum_{i=1}^{5} \theta_i\hat{w}_{it} + \varepsilon_t^* \qquad (20)$$

Since according to equation (17), $\hat{x}_{it} = x_{it} - \hat{w}_{it}$, we can then rewrite equation (20) as:

$$y_t = \beta_0 + \sum_{i=1}^{5} \beta_i x_{it} + \sum_{i=1}^{5} (\theta_i - \beta_i)\hat{w}_{it} + \varepsilon_t^* \qquad (21)$$

If there is no specification error for x_{it}, $\theta_i = \beta_i$. In the opposite case, $\theta_i \neq \beta_i$, and the coefficients of the residuals terms $\hat{w}_{it}$ are significantly different from 0.

A significantly positive estimate of $(\theta_i - \beta_i)$ indicates that the estimated coefficient of the corresponding explanatory variable x_{it} is overstated by OLS regression. In this case, the estimated coefficient for this variable in equation (21) will decrease compared to the OLS one. On the other hand, if the estimated coefficient $(\theta_i - \beta_i)$ is significantly negative, it suggests that the estimated coefficient of the corresponding explanatory variable x_{it} is understated by

OLS, and consequently, the estimated coefficient for this variable will increase in equation (21). In other respect, the estimated coefficients β_i are identical to those produced by TSLS procedure with the same instruments (Spencer and Berk 1981), except that, compared to a strict TSLS, equation (21) also provides additional information which proves quite helpful when estimating the accruals.

In the procedure we propose to test for specification errors, we first regress the observed explanatory variables x_{it} on the instruments vector to obtain the residuals $\hat{w}_{it}$. Then, we regress y_t on the observed explanatory variables x_{it} and on these residuals $\hat{w}_{it}$. This is an auxiliary (or artificial) regression we just described. If the coefficient of the residuals associated to an explanatory variable is significantly different from 0, we infer the presence of a specification error. In this case, a *t* test is used to assess the severity of the specification error. To our knowledge, such a test has never been used in this context. Usually, a Wald test (*F* test) is performed to check whether the whole set of $(\theta_i - \beta_i)$ coefficients is significantly different from zero, but this ignores the case of specification errors associated to a *specific* subset of explanatory variables.

We can generalize the former procedure to the case of *k* explanatory variables with our modified Hausman regression. Let **X** be a *(n x k)* matrix of explanatory variables not orthogonal to the innovation, and let **Z** be a *(n x s)* matrix of instruments (*s*>*k*). We regress **X** on **Z** to obtain $\hat{\mathbf{X}}$:

$$\hat{\mathbf{X}} = \mathbf{Z}\hat{\boldsymbol{\theta}} = \mathbf{Z}(\mathbf{Z'Z})^{-1}\mathbf{Z'X} = \mathbf{P_Z X} \qquad (22)$$

where $\mathbf{P_Z}$ is the “predicted value maker”. Having run this regression, we can compute the matrix of residuals $\hat{\mathbf{w}}$:

$$\hat{\mathbf{w}} = \mathbf{X} - \hat{\mathbf{X}} = \mathbf{X} - \mathbf{P_Z X} = (\mathbf{I} - \mathbf{P_Z})\mathbf{X} \qquad (23)$$

and perform the following artificial regression:

$$\mathbf{y} = \mathbf{X\beta} + \hat{\mathbf{w}}\boldsymbol{\lambda} \qquad (24)$$

A F test on the $\boldsymbol{\lambda}$ coefficients indicates whether the $\hat{\mathbf{w}}$ are significant as a group. But we also introduce a t test on each individual coefficients to check whether the corresponding β is understated or overstated. The vector of $\boldsymbol{\beta}$ estimated in equation (24) is identical to the TSLS estimates, that is:

$$\boldsymbol{\beta} = \boldsymbol{\beta}_{\mathbf{IV}} = \left(\mathbf{X'P_Z X}\right)^{-1}\mathbf{X'P_Z y} \qquad (25)$$

We apply the specification error method just described to several accruals models, among others, to model III, which is essentially the Kothari et al. (2005) model where the ROA is replaced by Tobin's q. To detect specification errors in these accruals models, we run two sets of regressions. For example, consider model III (i.e. the Tobin's q augmented accruals model). Following Kothari et al (2005), we first run the two OLS regressions using equations (9) and (11), for long term and short term accruals respectively. Second, we run the corresponding Hausman-C artificial regressions:

$$\frac{TA_{it}}{A_{i,t-1}} = \beta_1^*\left(\frac{1}{A_{i,t-1}}\right) + \beta_2^*\frac{PPE_{it}}{A_{i,t-1}} + \beta_3^*\frac{\Delta Sales_{it}}{A_{i,t-1}} + \beta_4^*\frac{q_{it(or\ i,t-1)}}{A_{i,t-1}} + \beta_5^*\frac{CF}{A_{i,t-1}} + \sum_{i=1}^{5}\varphi_i\hat{w}_{it} + \varepsilon_t^* \qquad (26)$$

$$\frac{TA_{it}}{A_{i,t-1}} = \beta_1^*\left(\frac{1}{A_{i,t-1}}\right) + \beta_3^*\frac{\Delta Sales_{it}}{A_{i,t-1}} + \beta_4^*\frac{q_{it(or\ i,t-1)}}{A_{i,t-1}} + \beta_5^*\frac{CF}{A_{i,t-1}} + \sum_{i=1}^{5}\varphi_i\hat{w}_{it} + \varepsilon_t^* \qquad (27)$$

The estimated coefficients φ_i allow the detection of specification errors, and their signs indicate whether the corresponding variable is overstated or understated in the OLS regression. Equations (26) and (27) represent the generalized version of the augmented accruals model. As previously mentioned, the β^* estimated in these equations are equivalent to the TSLS estimates. But they provide additional information about the severity of the specification errors. Indeed, the φ_i can in fact be considered as a measure of bias of the sensitivity of accruals to the ith explanatory variable. If φ_i is positive, it means that the sensitivity to the ith regressor is overstated in the OLS regression. The β associated to this variable will thus decrease in the artificial regression. And vice-versa if φ_i is negative. Moreover, according to our previous developments, we expect a high positive correlation between $\hat{\beta}_i - \hat{\beta}_i^*$, (the estimated error on the coefficient of variable *i*), and $\hat{\varphi}_i$, the estimated coefficient of the corresponding artificial variable $\hat{w}_i$.

We can sum up the former arguments using the following empirical equation:

$$Spread_i = \pi_0 + \pi_1 \varphi_i + \varsigma_i \qquad (28)$$

where $Spread_i = \hat{\beta}_i - \hat{\beta}_i^*$. According to equation (28), φ may thus be viewed as an indicator of overstatement or understatement of the OLS estimation for the coefficient of the ith explanatory variable. That constitutes our variant of the original Hausman test. The goodness of fit of equation (28) provides information about the severity of the specification errors for an explanatory variable.

From equation (12), we obtain the residuals which are introduced in equation (13) to compute the w_i. Equation (29) obtains for long term accruals:

$$TA_{it} = \alpha_s^* \left(\frac{1}{A_{i,t-1}} \right) + \beta_s^* PPE_{it} + \delta_s^* \Delta REV_{it} + \theta^* q_{it(or\ i,t-1)} + \sum_{i=1}^{4} \varphi_i \hat{w}_{it} + \varepsilon_t^* \qquad (29)$$

The corresponding short term accruals equation reads

$$TA_{it} = \alpha_s^* \left(\frac{1}{A_{i,t-1}} \right) + \delta_s^* \Delta REV_{it} + \theta^* q_{it(or\ i,t-1)} + \sum_{i=1}^{4} \varphi_i \hat{w}_{it} + \varepsilon_t^* \qquad (30)$$

This equation is proposed as a new benchmark to tackle the problem of specification errors. As shown in the following section, the instruments defined by **Z** are quite good. In other respects, these estimators have the advantage of requiring no extraneous information to the model.

2.3 Data

We use a sample composed of the firms registered in the S&P500 index. The observations are retrieved from the American **COMPUSTAT** database. Data are annual and run from December 1989 to December 2006, for a total of 10000 pooled observations. As previously done by other researchers in this literature (e.g. Kothari et al., 2005), we exclude firms having too few observations.

Since the objective of this study is to shed light on the relationship between accruals and key investment variables, instead of analyzing industrial sectors individually, we focus our attention on representative firms. We thus adjust firm data for size, and run our regressions using pooling methods. Specific industry factors are accounted for in the augmented version of the discretionary accruals models using firm microeconomic data like the employment level. Firm pooling also offers the advantage of a more parsimonious approach for testing the presence of measurement errors when estimating accruals models.

Insert table 1 here

Table 1 provides information on the correlation between the variables used in this study. At first glance, this table shows that some explanatory variables might present a significant degree of correlation with each other, which might cause some multicollinearity in regressions. For instance, the correlation between *PPE* and *CF* is about 0.7. Two other variables which are quite obviously related are *TAXES* and *PPE,* and *TAXES* and *CF*, the respective correlation coefficients between these variables being 0.59 and 0.73. Consequently, we have to study accruals as long-term investments but also have to examine a second round of our regressions excluding *PPE*. This precaution is rarely considered in the literature, as standard accruals models often resort to this variable as an explanatory factor. We thus consider two equations, (2) and (4), for computing total accruals, featuring a long-term and short-term version respectively. The variables used to compute accruals have already been defined earlier.

3. Results

3.1 OLS Estimations

Table 2(a) provides the OLS estimation of our three long term accruals models, corrected for heteroskedasticity to treat size effects. Based on the adjusted R^2 (at 0.74, 0.77 and 0.80 for the three models, respectively) the equations seem to perform quite well. The best model in terms of adjusted R^2 is model III. In the equation, except for *ΔSales*, all the coefficients are significant at the 99% confidence level. The Durbin-Watson are quite similar in the [1.98, 2.12] range. In light of the R^2, there thus seems to be no autocorrelation or non-stationary residuals problems, which would give rise to spurious regressions.

Insert Table 2(a) about here

When comparing the coefficients of models II and III, first note the similarities in terms of magnitude and signs of the coefficients. For instance, the coefficient of PPE is -0.0514 in model II and -0.0554 in model III. We obtain the same results for the estimated coefficients of *CF,* respectively 0.3336 and 0.3086 in models II and III − and *ΔSALES*, 0.0005 versus 0.0003. However for model I, the estimated coefficient of *PPE* is much larger, at -0.750. This finding derives from the omission of cash-flow in model I, and is a clear indication of the key role played by this explanatory variable to properly characterize accruals. For the same reason, the coefficient of *ΔSALES*, at 0.0032 in model I, is also larger than its counterparts in models II and III. Our models indicate that accruals are indeed sensitive to cash-flows, which tends to suggest that market imperfections and financial constraints influence investment decisions. In this respect, our results confirm that markets imperfections play a role as suggested many times in the literature (e.g. Gilchrist and Himmelberg 1995), and here analyzed in the context of accruals and short-term investment.

The novelty we introduce in this kind of setting, Tobin's *q*, delivers quite interesting results. Consistent with the investment theory, this variable should positively impact accruals, impacting positively investment. Our results seem to confirm this relation, the Tobin's *q* coefficient being significant at the 99% confidence level.

Insert Table 2(b) about here

Table 2(b) reports the corresponding results for the three short-term versions of the models where *PPE* is removed. In spite of the omission of the *PPE* variable in the regressors and the associated removal of the depreciation component of accruals, the results remain very comparable to those of table 2(a), both in terms of sign and magnitude of the coefficients.

3.2 Haus-C Estimations

Tables 3(a) and 3(b) present the results of Haus-C estimations for the three models corrected for heteroskedasticity. Regarding the long-term versions of the models, Table 3(a) shows that the Haus-C regressions systematically yield lower R^2, 0.28, 0.48 and 0.39 respectively. This suggests that measurement errors in the explanatory variables cause significant biases in the OLS regressions. Furthermore, most variables are significant at the 95% confidence level, but looking at the significance levels, model III seems to outperform the other models. Finally, for the three models, the levels of the Durbin-Watson do not seem to indicate any significant autocorrelation.

Insert Tables 3(a) and 3(b) about here

Given these results and the fact that they are quite comparable among the various models, we focus mainly on model III to analyze further the measurement errors. As expected, the $\hat{\varphi}_i$ indicate the presence of substantial measurement errors for all explanatory variables. First, the most commonly used explanatory variables of accruals, *ΔSALES, PPE* and $1/A_{i,t-1}$, seem to be measured with significant error. Incidentally, the coefficient of *ΔSALES* changes substantially from one model to another, and it seems to be quite contaminated. For model III, its $\hat{\varphi}_i$ is equal to -0.0612, significant at the 99% confidence level. While, for the OLS estimation, the coefficient of this variable is almost 0, this suggests a severe understatement in the OLS estimation. The coefficient of *ΔSALES* is also significant in models I and III, but only after correction for measurement errors. This finding is in line with most empirical studies using the Jone's model of non-discretionary accruals. There is also a significant measurement error for the *PPE* variable, its $\hat{\varphi}_i$ being equal to 0.0840, significant at the 99% confidence level. In this case, there is an overstatement of the coefficient in the OLS regression.

Compared to the OLS results, the estimated coefficients of models I and III are of the same order of magnitude, and also comparable in sign. For example, the coefficient associated to *PPE* is -0.0142 in model I and -0.0786 in model III. For model II however, the coefficient of *PPE* is almost double, at -0.1605, with the right sign. This discrepancy can also be interpreted as symptomatic of the presence of measurement errors, as recorded by the $\hat{w}_{2t}$ coefficient −

thereafter called the coefficient of understatement or overstatement – at 0.1455, and significant at the 99% confidence level. Indeed, being at -0.0514 in the corresponding OLS estimation, this coefficient (significant at the 99% confidence level) suggests that the impact of *PPE* is overstated in the OLS estimation.

More importantly, based on the Haus-C method , if we look at the cash-flow variable in models II and III, the coefficient doubles when Tobin's q is introduced[7]. In model III, the cash-flow coefficient is equal to 0.2866, significant at the 99% confidence level, with a coefficient of understatement of -0.3182 significant at the 99% level, whereas in model II, from which Tobin's q is absent, the coefficient is down to 0.1435 (still significant at the 99% level), with a coefficient of understatement of -0.1313, also significant at 99% level. Furthermore, the Haus-C results also confirm the expected positive relationship between accruals and Tobin's q, the influence of this regressor being significant at the 99% confidence level. In this respect, the coefficient of Tobin's q estimated by OLS is about 4.0897 in model III, but much higher at 6.3103, significant at 95%, if estimated with the Haus-C procedure. The error adjustment variable, $\hat{w}_{5t}$, is equal to 5.9554, and significant at the 99% confidence level, suggests a substantial measurement error on this variable. This is consistent with our conjecture that this proxy of marginal q variable is badly measured with a severe error. After correcting for measurement errors, the incorporation of Tobin's q in the accruals model increases the sensitivity of accruals to the other explanatory variables. For instance, the impact of cash-flows doubles. But at this point we cannot infer the predominance of cash-flows over Tobin's q as

[7] Our study contradicts the results of the article of Erickson and Whited (2000), one of the few studies on the impact of financial constraints on investments using GMM. After accounting for measurement errors, they found no relationship between cash-flows and investment, rehabilitating the role of Tobin's q as the primary explanatory variable of investment. Note however that, for achieving this conclusion, the authors use classical instruments and not higher moments and do not focus on short-term investment as we do. See also the study of Hovakimian and Hovakimian (2009) for a different picture of the sensitivity of investments to cash-flows.

previous studies adjusting for Tobin's *q* measurement errors do (Fazzari et al. 1988, Caballero 1999) with much more cumbersome numerical techniques than ours. Indeed, we use cumulants for correcting measurement errors in our GMM setting, a novel procedure in the accruals literature.

Table 3(b) summarizes the results obtained from the short-term versions of the accruals models. Not surprisingly, since model III better reflects the investment nature of accruals, the results confirm that it is a preferable specification if we focus on investment In other respects, the short-term models perform poorly in the Haus-C estimations. For example, the adjusted R^2 is double when *PPE* is included in the long-term model compared to the case where *PPE* is absent. In the short-term version of the models, the magnitude of all coefficients is altered, although the signs remain correct. In other words, when going from the long-term version (with *PPE*) to the short-term one, the R^2 is halved and the coefficients drop. However the specification remains robust, in the sense that, qualitatively, the explanatory variables are still significant and of the right sign. Interestingly, when excluding *PPE* from model III (i.e. in the short-term version of model III), the influence of Tobin's *q* is strengthened while the impact of cash-flows is divided by three, and its coefficient is only significant at the 90% confidence level. Quite counter-intuitively, everything works as if the classical theory of investment applied more at short horizons, whereas financial constraints would have more influence in the long-run. Not only is the influence of Tobin's *q* relative to cash flow higher in the short-term models, but it is even larger if we account for measurement errors. Actually, going from OLS to Haus-C, the coefficient increases from 5.22 to 8.66. Hence, when accounting for the endogeneity problem, the explanatory power of cash-flows seems weaker in short-term accruals models. This result could be of the same nature as the one reported by Erickson and

Whited (2000) for long-term investment. If we account for measurement errors, no relationship seems to persist between cash-flows and investment. This would rehabilitate the role of Tobin's *q* as the primary explanatory variable of investments. The finding could also be considered in line with the recent literature which suggests that the investment-cash-flows sensitivity has actually decreased consecutive to the on-going financial deepening process (e.g. Agca and Mozundar 2008, Brown and Petersen 2009). One explanation is that as external financing becomes more available, firms financial constraints are increasingly relaxed, and the role of cash-flows as a cushion for financing lowered. Another argument is that firms hold more cash because their cash-flows streams tend to be riskier, as evidenced by Bates et al. (2009). Therefore, the precautionary demand for cash increases and the sensitivity of accruals to cash-flows is reduced.

More pragmatically, there is a simpler way to reconcile our finding with investment theory. Regardless of what was found elsewhere in the literature about long-term investment, we have to bear in mind that, in the short-term accruals models, there is no *PPE*. Since this variable, as often documented in previous studies, is highly correlated with cash flows (c.f. Table 1), it should not be so surprising to find cash flows more significant in the long-term version of the models, when *PPE* is introduced in the accruals models. In other words, the lack of significance of cash flows in the short-term accruals models, or, to put it differently, the increased significance of Tobin's *q* in the *short-run*, is simply an artefact of the correlation of *PPE* with cash-flows.

3.3 Augmenting the Jones Model with Firm Microeconomic Data

Since the investment perspective provides interesting insight about accruals, it is worth studying further the role of variables which are likely to impact accruals or investments. Furthermore, instead of adopting a global approach to the study of accruals as done in our paper, many researchers divide accruals by industrial sectors since the behaviour of accruals might differ from one sector to another. Adding microeconomic data to our models might help control for the firm dimensions of accruals. We thus examine the impact of three additional variables, employment (*EMP*), taxes (*TAXES*) – both corrected for heteroskedasticity – and gross total return (*ROA*)[8]. Indeed, the role of the later is often analyzed in this kind of studies (e.g. Kothari et al. 2005), and considered here in combination with Tobin's q, another measure of return.

The estimated equation reads:

$$\begin{aligned} \frac{TA_{it}}{A_{i,t-1}} &= \beta_1\left(\frac{1}{A_{i,t-1}}\right) + \beta_2 \frac{\Delta Sales_{it}}{A_{i,t-1}} + \beta_3 \frac{CF_{it}}{A_{i,t-1}} + \beta_4 \frac{q_{it}}{A_{i,t-1}} + \beta_5 \frac{EMP_{it}}{A_{i,t-1}} + \ldots \\ &+ \beta_6 \frac{TAXES}{A_{i,t-1}} + \beta_7 ROA_{it} + \varepsilon_{it} \end{aligned} \tag{31}$$

We compare the TSLS-hm estimation of this model, which accounts for measurement errors, with OLS. Table 4 and 5 report the estimated coefficients of equation (31), the OLS method and the TSLS-hm respectively. Both estimation techniques yield strong results as measured by the adjusted R^2 and DW.

Insert tables 4 and 5 about here

[8] Note that *ROA* might be seen as a substitute to Tobin's q in our kind of setting.

Note that the results are similar with both estimation methods so we only discuss the case of the TSLS-hm experiment. A first glance at table 5 reveals that most of the relevant variables discussed in the literature - i.e. *ΔSales*, *CF*, and Tobin's *q* - have the expected sign and are significant at the 95% confidence level. The influence of our two keys financial, *CF* and Tobin's *q*, is lowered when applying TSLS-hm instead of OLS. For instance, the *CF* coefficient decreases from 0.39 to 0.27, and the Tobin's *q* coefficient drops from 5.80 to 4.28. This confirms again that the respective weights of these two variables is overstated in the OLS run.

The negative sign of *EMP/ASSET (-1)* indicates that firms with a high employment ratio tend to invest less. Intuitively, this might be related to the fact that, by definition, firms with a high employment ratio are more labor-intensive and thus require less working capital. The positive sign obtained for the *TAXES* variable suggests that an increase in taxes induce firms to hold more working capital as a cushion, taxes reducing free cash-flows. Finally, in our model, return on assets (*ROA*) seems to have a small impact on accruals, likely because of the preponderance of Tobin's *q* in the equation. Regarding the sign of *ROA*, since investments should increase when performance, measured by return on assets, is higher, it is quite rational to find a positive sign in both regressions.

A Wald test reveals that these variables - *EMP/ASSET (-1), TAXES/ASSET(-1),* and *ROA* - are significant as a group at the 95% level in the OLS run and at the 90% level with the TSLS-hm run. However, *EMP/ASSET (-1)* is individually the only variable significant at the 95% level in the OLS regression. Furthermore, *ROA* is the only significant variable (at the 90% confidence level) in the TSLS-hm estimation.

4. Conclusion

In this paper, we apply an econometric method based on an improved Hausman artificial regression to account for measurement errors in accruals models. Our contribution is twofold. We introduce the Haus-C procedure and an optimal instrumental variables generator and apply this framework to accruals viewed through an investment perspective. This approach allows us to study the impact of financial constraints on accruals. We also consider microeconomic variables, as employment, taxes, and *ROA* which also influence accruals.

Some important econometric problems are related to the estimation of our augmented accruals models. A well-known issue relates to the difficulty in properly estimating Tobin's q given that it is not directly observable. As usually done in the investment literature, we rely on an average measure to proxy Tobin's q. There is thus an inherent measurement error related to the computation of this ratio. Ignoring the appropriate correction entails an empirical interaction[9] between cash-flows and Tobin's q which biases the estimated coefficients of both variables. We thus resort to a new estimation procedure to reduce this measurement error. Based on this methodology, we are able to detect serious measurement error problems in the basic Jones model and its augmented versions. Actually, the estimation of the augmented accruals model reveals that the differences between the TSLS-hm and OLS coefficients are substantial, which suggests the presence of significant measurement errors in all variables. Furthermore, when estimated with our method, the impact of Tobin's q is strengthened in model III compared to the findings of the standard OLS approach. We also confirm the influence of financial constraints, as measured by cash-flows, in this context, although their impact is reduced when introducing Tobin's q and accounting for measurement errors.

[9] Indeed, before correction for measurement errors, Tobin's q may embed information on future cash-flows. Cash-flows contain information on firm's value, an information that should only be found in Tobin's q if the regressors were completely orthogonal.

Many questions remain open to investigation. For example, the economic specification of the accruals model could be improved. We could think of a truly dynamic setting to study the reaction of accruals to aggregate shocks. This might proves particularly useful for portfolio managers because discretionary accruals is an important variable to forecast stocks returns. Our approach could also be applied to panels. That would shed light on the fixed and random effects at play. Another obvious shortcoming on most studies found in the accruals literature is that they rarely resort to proper econometric tests like unit root tests or panel data cointegration tests. This is left for future work.

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TABLES

Table 1 Variables Correlation Matrix

	ACCRU	CF	DELT_SALES	EMP	GRO_TOTRET	PPE	RATIO_INV_ASS	TAXES	Q
ACCRU	1.00	0.30	-0.04	0.09	0.02	-0.02	-0.21	0.37	0.14
CF	0.30	1.00	0.04	0.33	-0.01	0.70	0.12	0.73	-0.01
DELT_SALES	-0.04	0.04	1.00	0.02	-0.01	0.07	0.00	0.03	-0.01
EMP	0.09	0.33	0.02	1.00	0.02	0.39	0.10	0.27	-0.05
GRO_TOTRET	0.02	-0.01	-0.01	0.02	1.00	-0.02	-0.05	-0.01	0.04
PPE	-0.02	0.70	0.07	0.39	-0.02	1.00	0.41	0.59	-0.10
RATIO_INV_ASS	-0.21	0.12	0.00	0.10	-0.05	0.41	1.00	0.00	-0.21
TAXES	0.37	0.73	0.03	0.27	-0.01	0.59	0.00	1.00	0.02
Q	0.14	-0.01	-0.01	-0.05	0.04	-0.10	-0.21	0.02	1.00

Table 2(a) OLS estimation of the three basic models of accruals represented respectively by equations (5), (7) and (9).

	Model I	Model II	Model III
$1/A_{i,t-1}$	-0.1084	2.7080***	0.3892***
$PPE_{it}/A_{i,t-1}$	-0.750***	-0.0514***	-0.0554***
$\Delta SALES_{it}/A_{i,t-1}$	0.0032	0.0005	0.0003
$CF_{it}/A_{i,t-1}$		0.3336***	0.3086***
$q_{it}/A_{i,t-1}$			4.0897***
Adjusted R^2	0.74	0.77	0.80
DW	2.02	2.12	1.98

Table 2(b) OLS estimation of the three basic models of accruals represented respectively by equations (6), (8) and (11)

	Model I	Model II	Model III
$1/A_{i,t-1}$	-0.1975***	-0.2032***	-0.1338***
$\Delta SALES_{it}/A_{i,t-1}$	0.0040***	0.0086***	0.0047
$CF_{it}/A_{i,t-1}$		0.3595***	0.2234***
$q_{it}/A_{i,t-1}$			5.2361***
Adjusted R^2	0.71	0.73	0.74
DW	2.04	1.93	2.23

Table 3(a) Haus-C estimations of the three basic models of accruals given by equation (26)

	Model I	Model II	Model III
$1/A_{i,t-1}$	1.3504***	0.2161***	0.6714***
$PPE_{it}/A_{i,t-1}$	-0.0142	-0.1605***	-0.0786***
$\Delta SALES_{it}/A_{i,t-1}$	0.0175***	0.0021	0.0165***
$CF_{it}/A_{i,t-1}$		0.1435***	0.2866***
$q_{it}/A_{i,t-1}$			6.3103***
$\hat{w}_{1t}$	7.9290***	-0.8610*	7.2810***
$\hat{w}_{2t}$	0.0150	0.1455***	0.0840***
$\hat{w}_{3t}$	-0.0778***	0.0104***	-0.0612***
$\hat{w}_{4t}$		-0.1313***	-0.3182***
$\hat{w}_{5t}$			9.6702***
Adjusted R^2	0.28	0.48	0.39
DW	2.10	1.20	2.11

Table 3(b) Haus-C estimations of the three basic models of accruals given by equation (27)

	Model I	Model II	Model III
$1/A_{i,t-1}$	1.6067***	1.4031***	0.4142**
$\Delta SALES_{it}/A_{i,t-1}$	0.0787***	0.0647***	0.0622**
$CF_{it}/A_{i,t-1}$		0.3835***	0.1290*
$q_{it}/A_{i,t-1}$			8.6652***
$\hat{w}_{1t}$	3.1363***	3.2952***	5.6220***
$\hat{w}_{2t}$	-0.0749***	-0.0589***	-0.0613***
$\hat{w}_{3t}$		-0.4926	-0.2492***
$\hat{w}_{4t}$			-11.1660***
Adjusted R^2	0.13	0.18	0.21
DW	2.06	2.02	2.04

Table 4 Augmented Jones' model with microeconomic variables

	Coefficient	t-Statistic	Prob.
1/ASSET(-1)	-0.5173	-2.40	0.02
DELT_SALES/ASSET(-1)	0.0097	2.25	0.03
CF/ASSET(-1)	0.3900	3.00	0.00
TOBINQ/ASSET(-1)	5.8043	3.21	0.00
EMP/ASSET(-1)	-14.3180	-2.91	0.00
TAXES/ASSET(-1)	0.1901	0.40	0.69
ROA	0.0000	0.39	0.70
Adjusted R-squared	0.72		
Durbin-Watson stat	2.04		

Table 5 TSLS-hm estimation of the accruals economic model

	Coefficient	t-Statistic	Prob.
1/ASSET(-1)	-0.4098	-1.89	0.06
DELT_SALES/ASSET(-1)	0.0100	2.26	0.02
CF/ASSET(-1)	0.2743	1.98	0.05
TOBINQ/ASSET(-1)	4.2788	2.30	0.02
EMP/ASSET(-1)	-8.9300	-1.53	0.13
TAXES/ASSET(-1)	0.6848	1.19	0.24
ROA	0.0003	1.70	0.09
Adjusted R-squared	0.72		
Durbin-Watson stat	2.01		