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ABSTRACT

Accruals models have been estimated using a variety of approaches, but the industry-based cross-sectional approach currently seems to be the standard method. This estimation approach cannot be easily used in the vast majority of European countries where several industry groups do not have sufficient yearly observations. Using data from France, Germany, Italy and the UK, we artificially induce earnings manipulations to investigate how the ability to detect those manipulations through accruals models is affected by the use of different industry classifications. Moreover, we propose an alternative estimation approach based on a data-driven statistical procedure that provides an optimal choice of estimation samples. Our analyses show that enlarging the industry classification and/or pooling observations across years reduces the probability of discovering earnings manipulations but allows for the estimation of abnormal accruals (AA) for more firms. The data-driven approach, however, in most cases outperforms the industry-based estimation approaches without sample attrition. This result suggests that there is still ample room for improving the accruals model estimation process for capital markets of European countries. Furthermore, the analysis documents which accruals model outperforms the others in each of the four countries and the probabilities to detect earning management in a high variety of circumstances.

1. Introduction

Since pioneering studies in the late 1980s began to investigate earnings management activity (Healy, 1985), the literature has analysed the performance of different accruals models (Alcarria Jaime & Gill de Albornoz Noguer, 2004; Dechow, Sloan, & Sweeney, 1995; Peasnell, Pope, & Young, 2000; Peek, Meuwissen, Moers, & Vanstraelen, 2013). However, scant attention has been paid to both the effects of the estimation approaches on an accruals model's performance and to the way it changes when capital markets of different countries are analysed.[1]

Accruals models are traditionally estimated over firm-specific time-series (Jones, 1991) or more frequently cross-sectionally by year and industry (DeFond & Jiambalvo, 1994). For instance, in US studies the most commonly used industry classification is the two-digit Standard Industrial Classification (SIC) code, whereas researchers investigating UK listed firms frequently employ the Datastream Level 6 industry classifications (Athanasakou, Strong, & Walker, 2009; Gore, Pope, & Singh, 2007; Peasnell et al., 2000; Young, 1999). On the other hand, when studying countries with smaller capital markets, researchers use industry classifications less detailed than the two-digit SIC code and Datastream Level 6 (Alcarria Jaime & Gill de Albornoz Noguer, 2004; Saleh & Ahmed, 2005; Van Tendeloo & Vanstraelen, 2008). This happens because partitioning the available observations by year and a highly detailed industry classification results in several estimation samples without a minimum number of observations to estimate accruals models and it causes a severe loss of observations, as confirmed by Ecker et al.'s (2013) extensive analyses. The level of detail of the industry classification employed is relevant because any estimation approach implicitly assumes that all firms within the chosen classification have homogenous Accrual-Generating Processes (AGPs), and this assumption is proven not to hold always true for some two-digit SIC code industries (Dopuch, Mashruwala, Seethamraju, & Zach, 2012). Therefore, this evidence raises the question whether using industry classifications less detailed than two-digit SIC code affects the probability to detect earnings manipulations through accruals models.

The objective of this study is twofold. First, we aim at investigating how the estimation approach used to estimate accruals models affects the ability to detect earnings management activities in four major European member states (namely France, Germany, Italy and the UK). The capital markets of these four countries differ in size and thus the estimation of accruals models is differently affected by sample attrition. Second, we evaluate how improving the grouping criterion employed to identify the estimation samples may increase the probability of detecting earnings manipulations. This is attained by employing an alternative estimation approach based on a data-driven statistical procedure, called mixture (MIX). The improvement of existing accruals model specifications, on the other hand, is beyond the scope of this study, as well as the development of new accruals models.

In order to evaluate the ability to detect earnings manipulations of different estimation approaches, we perform a simulation study where we artificially manipulate reported earnings and we measure the frequency with which each model produces Type I and Type II errors (Dechow et al., 1995). The simulation results provide evidence that the estimation approach significantly affects the ability to detect earnings management with a pattern consistent across countries. Among the industry-based estimation approaches, the cross-sectional by year and two-digit SIC code (2SICy) appears to be the best approach. Moreover, it seems that moving from two-digit SIC codes to a less detailed industry classification hampers the ability to detect earnings manipulations, even if it often allows researchers to test their hypotheses using larger study samples. The MIX approach always appears to improve the ability to detect earnings manipulations through accruals models when compared to industry-based estimation approaches.

This study contributes to the earnings management literature in three dimensions. First, it shows how the probabilities to detect earnings manipulations might vary across European countries. Second, our results outline that the estimation approach and the industry classification employed are choices as important as the choice of accruals model in deciding the research design. Finally, the performance of the MIX approach provides evidence that

grouping criteria alternative to industry classifications may increase significantly the probability to detect earnings manipulations.

The remainder of the article is structured as follows. Section 2 describes the estimation approaches proposed by the accounting literature. Section 3 illustrates the simulation procedure, the accruals models and the data. Estimation results and *ex post* interpretations of the grouping identified by the data-driven estimation approach are presented in Section 4. Section 5 describes simulation results and Section 6 concludes the article.

2. Industry-based estimation approaches versus the MIX approach

The choice of any criterion used to identify the estimation samples for accruals models implicitly relies on a homogeneity assumption, according to which firm observations within each estimation sample should share uniform AGPs, otherwise the estimates could be biased toward unpredictable directions and/or the ability to detect earnings manipulations could be reduced substantially (McNichols, 2000). In her seminal paper, Jones (1991) estimated her innovative accruals model specification over firm-specific time-series by defining one estimation sample for each firm in study sample. This approach provides a reasonable assurance that the homogeneity assumption holds. However, requiring a minimum number of observations (e.g., 10) for each firm in the study sample may induce a survival bias (Jeter & Shivakumar, 1999) and severely constrains the size of the sample over which the research hypothesis can be tested. In response, DeFond and Jiambalvo (1994) estimate the Jones model cross-sectionally by year and industry (i.e., two-digit SIC code) to maximise the size of their study sample. Kothari, Leone, and Wasley (2005) propose a return on assets (ROA)-matched firm approach to control for the correlation between AAs and firm performance. In other studies, the accruals models are estimated on samples where available observations are pooled either across years (Erickson & Wang, 1999), or across countries (Chaney, Faccio, & Parsley, 2011; Haw, Hu, Hwang, Wu, & Wysocki, 2004) to circumvent the lack of data availability. Finally, Ecker et al. (2013) propose to identify estimation samples based on the similarity of lagged total assets.

Thus far, the most popular estimation approach is the cross-sectional by year and industry approach, and the SIC codes at two-digit level are the most common industry classification employed. This approach has several advantages: it is proven to be more effective than the time-series estimation approach in detecting earnings management (Bartov, Gul, & Tsui, 2000), it does not induce any survival bias (Kang & Sivaramakrishnan, 1995) and it is easy to employ. The implicit assumption is that all the firms within the same industry have a homogeneous AGP in any given year. However, the cross-sectional 2SICy estimation approach has two weaknesses. First, Dopuch et al. (2012) show that the assumption of a homogeneous AGP does not hold in several two-digit SIC code groups, and consequently, in those industries there is a higher likelihood of finding large absolute AAs. Second, the use of accruals models estimated cross-sectionally by 2SICy is not practical or even possible in cross-country studies, due to both the lack of sufficient observations in each two-digit SIC code (Ecker et al., 2013) and the differences in the fit of accruals models across countries (Wysocki, 2004). Our data show that, if a researcher wishes to investigate the Italian capital market, which is the smallest in our study but one of the largest in the EU, they will estimate AAs for only 43% of the potentially available observations using the 2SICy approach. In response, either an industry classification wider than the two-digit SIC code is used to estimate the accruals models cross-sectionally (e.g., Athanasakou et al., 2009;

Gore et al., 2007; Lapointe-Antunes, Cormier, Magnan, & Gay-Angers, 2006; Lehmann, 2016; Sáenz González & García-meca, 2014; Saleh & Ahmed, 2005; Simpson, 2013; Van Tendeloo & Vanstraelen, 2008) or alternative techniques are employed to identify AAs (e.g., Capalbo, Frino, Mollica, & Palumbo, 2014; DeFond & Park, 2001; Francis & Wang, 2008; Ittonen, Johnstone, & Myllymäki, 2015; Jansen, Ramnath, & Yohn, 2012; Zerni, Haapamäki, Järvinen, & Niemi, 2012).

Given the objective of our study, we estimate accruals models using four industry-based approaches and a new estimation approach that does not rely on any industry classification in four European countries. The first estimation approach classifies firm-observations by year and two-digit SIC code (2SICy). In the second approach, firm observations are classified by year and a higher level of industry classification. Operationally, we identify the estimation samples based on the year and the following seven sectors (SECTy): Agriculture (two-digit SIC codes from 01 to 09), Mining & Construction (two-digit SIC codes from 10 to 17), Manufacturing (two-digit SIC codes from 20 to 39), Transportation & Utilities (two-digit SIC codes from 40 to 49), Wholesale & Retail Trade (two-digit SIC codes from 50 to 59), and Services (two-digit SIC codes from 70 to 89).

We test a modified 'pooled' version of the two above illustrated approaches where firm observations are pooled across years. In particular, the third estimation approach tested identifies the estimation samples based only on the two-digit SIC code, without considering the year (2SICp), and the fourth estimation approach identifies the estimation samples only on the basis of the sector, as previously defined (SECTp).

Finally, the MIX approach classifies firm observations in homogeneous estimation samples using a data-driven procedure. Once an accruals model is selected, for instance the Jones model, the MIX approach derives a useful division of observations in clusters (i.e., the equivalent of our estimation samples), in which both the number of the clusters and the parameters are to be determined. The rationale is that each cluster will encompass firm observations having AGPs that are as homogeneous as possible, with reference to the specific accruals model chosen, because the number and composition of clusters are determined to maximise a fit criterion. With respect to traditional approaches in which AGPs are assumed to be uniform within each industry classification and, in the case of cross-sectional approaches, within each fiscal year, the MIX approach relaxes this implicit assumption in favour of the rationale that firms have G unknown AGPs, regardless of the industry they have been classified into. In other words, within the MIX approach, each observation may be generated by one of G alternative underlying accruals models involving the same functional form with identical explanatory variables but with different parameters. For instance, if the Jones specification is chosen, the MIX approach groups firm observations in G estimation samples and provides estimates of G Jones models. For this reason, the MIX approach should provide an optimal, data-driven estimation samples composition that might indicate the degree to which the ability to identify earnings management could be increased by improving the estimation process.

The MIX approach is based on the statistical MIX model which has the following form:

$$p\left(A|X_1,\dots,X_S,\Theta\right) = \sum_{g=1}^{G} \pi_g N_g\left(A|X_1,\dots,X_S,\theta_g\right) \tag{1}$$

where:

A denotes the observed accruals;

$X_1,\ldots, X_S$ are the explanatory variables of the accruals model;

$p(.)$ is the marginal distribution density of A conditional on explanatory variables $X_1,\ldots, X_S$;

$\Theta = \left\{ \theta_g \right\}_{g=1}^{G}$ is the set of accruals model parameters and θ_g is the vector of model parameters of the g-th group;

$N_g(.)$ is the normal density of A conditional on explanatory variables $X_1,\ldots, X_S$ of the g-th group;

π_g represents the proportion of observations generated by the g-th class (with $\sum_{g=1}^{G} \pi_g = 1, \ \pi_g > 0, \forall g$).

The MIX approach modifies traditional, industry-based estimation procedures for accruals models as follows. First, all of the available observations are assigned to the G estimation samples by imposing the restriction that each estimation sample contains a minimum number of observations. Second, the accruals model is estimated jointly for all the identified estimation samples. Third, steps one to two are repeated through an iterative algorithm until the likelihood of model (1) cannot be further maximised (Leisch, 2004).

In this study, the sequence is initialised with three starting points representing the partitions of G estimation samples (where G = 3,…,15), and the solution that minimises the Akaike Information Criterion is chosen. Moreover, as a strategy for finding a reasonable solution, we implement the MIX as a pooled approach by forcing all of the yearly observations of each firm to be assigned to the same estimation sample. This constraint removes (or at least strongly reduces) the risk that the MIX identifies estimation samples in which firm–year observations are biased by the same type of earnings management. Because the earnings management activity technically consists of shifting non-cash earnings components from one period to another and usually discretionary accruals reverse in the near future (Dechow, Hutton, Kim, & Sloan, 2012), pooling together all of the observations of the same firm should prevent estimation samples biased towards a specific earnings management activity.

3. Experimental design

To assess and compare the ability of the selected estimation approaches to detect earnings manipulations, we run a simulation procedure over four different European countries using several accruals models.

3.1. Simulation procedure

We follow the research design proposed in several studies (e.g., Alcarria Jaime & Gill de Albornoz Noguer, 2004; Peasnell et al., 2000). To estimate the probabilities of Type I and Type II errors in the accruals model-based tests, we simulate artificial scenarios for different types and amounts of earnings manipulations and verify the frequency with which the null hypothesis of no earnings management is rejected when it is true or false, respectively. If an accruals model is well-specified, in the absence of any artificially induced earnings manipulation, the null hypothesis of no earnings management should not be rejected more often than the specified level of the test (e.g., 5%). The ability to detect earnings manipulations (i.e., the power of the accruals model-based test) is measured as the frequency with which the null hypothesis of no earnings management is rejected when it is false because we have artificially manipulated the reported earnings.

Operationally, we apply the following procedure separately for each combination of estimation approach, accruals model, and country. Hereafter, we refer to an 'estimation sample' as the group of firm–year observations used to estimate the accruals model and a 'study sample' as the group of firm–year observations for which AAs are calculated and over which the earnings management hypothesis is tested.

(1) We estimate the accruals model's parameters using one of the estimation approaches tested over the identified estimation samples using the available data. The observations in the estimation samples with fewer than eight observations are excluded from the procedure.

(2) Among the observations for which AAs can be potentially estimated, we randomly select 100 firm–year observations without replacement as the study sample. Then, we create a dummy variable (PART) that equals one for five randomly selected observations within the study sample and zero for the other 95 observations. To show how the size and composition of the study sample affect the ability to detect earnings manipulations, for the UK data only, we increase both the number of observations in the study sample to 1000 and the percentage of the manipulated observations (i.e., observations for which PART=1) to 20%.

(3) We perform the following type of earnings manipulation on the five observations for which PART=1[2]: we simulate the situation in which managers increase reported earnings by delaying the recognition of expenses other than bad debt provisions to future periods (i.e., expense manipulation). In practice, this behaviour may materialise in different technical ways. For instance, when costs that should be recognised as expenses of the period are capitalised and recognised as assets on the balance sheet, even if they do not meet the asset definition, the net income of the period is overstated.[3] Operationally in our simulation, it is implemented by adding the assumed amount of earnings manipulation to the total accruals of the five selected firms. We test the earnings manipulation at different amounts ranging from 0% to 5% of lagged totalassets in increments of 1%.

(4) After each manipulation, we calculate AAs for all 100 firm–year observations in the study sample as the observed accruals minus the accruals predicted by the estimated accruals model.

(5) Finally, we test for earnings management by regressing the AA on the dummy variable PART over the study sample:

$$AA_j = \gamma + \delta \, PART_j + \varepsilon_j \text{ where } j=1,\ldots,100$$

Steps 2 to 5 are repeated 1000 times with a bootstrap. The probabilities of Type I and Type II errors are estimated using the frequency of rejection, averaged over all 1000 replications, of the one-sided t-test at the 5% level for the null hypothesis $\delta=0$, when the five observations for which PART equals one have not been manipulated (i.e., *no manipulation*) or have been manipulated.

It is worth noting that in the simulation procedure here employed, the artificially induced working capital accruals manipulations do not reverse.

3.2. Accruals models

We estimate the following four accruals models:

Jones (1991) model: $TA\_ind_{it} = \alpha + \beta_1 (1/\text{Total Assets}_{it-1}) + \beta_2 \Delta REV_{it} + \beta_3 PPE_{it} + \varepsilon_{it}$ (J)

Dechow et al. (1995) model: $TA\_ind_{it} = \alpha + \beta_1 (1/\text{Total Assets}_{it-1}) + \beta_2 (\Delta REV_{it} - \Delta REC_{it}) + \beta_3 PPE_{it} + \varepsilon_{it}$ (DSS)

Ball and Shivakumar (2006) model: $TA\_dir_{it} = \alpha + \beta_1 (1/\text{Total Assets}_{it-1}) + \beta_2 \Delta REV_{it} + \beta_3 PPE_{it} + \beta_4 \Delta CF_{it} + \beta_5 LOSS_{it} + \beta_6 LOSS_{it} * \Delta CF_{it} + \varepsilon_{it}$ (BS)

Modified Dechow and Dichev (2002) model: $TA\_dir_{it} = \alpha + \beta_1 CF_{i(t-1)} + \beta_2 CF_{it} + \beta_3 CF_{i(t+1)} + \beta_4 \Delta CF_{it} + \beta_5 LOSS_{it} + \beta_6 LOSS_{it} * \Delta CF_{it} + \varepsilon_{it}$ (MDD)

where:

TA_ind_{it} = scaled total accruals in period t calculated indirectly as the change in non-cash current assets less the change in current liabilities, excluding the short-term debts and the current portion of long-term debt, less depreciation and amortisation divided by lagged total assets;

$\text{Total Assets}_{it-1}$ = lagged total assets;

ΔREV_{it} = change in revenues scaled by lagged total assets;

PPE_{it} = property, plant, and equipment gross scaled by lagged total assets;

ΔREC_{it} = change in receivables scaled by lagged total assets;

TA_dir_{it} = total accruals in period t calculated directly as the difference between net income before extraordinary items and net cash flow from operating activities divided by lagged total assets;

ΔCF_{it} = change in net cash flow from operating activities divided by lagged total assets;

$LOSS_{it}$ = equals 1 if the change in net cash flow from operating activities < 0, zero otherwise;

CF_{it} = net cash flow from operating activities divided by lagged total assets.

3.3. Data

We analyse samples from four major European countries: France, Germany, Italy and the UK. Our samples consist of all of the non-financial listed firms for which data are available on DATASTREAM/WORLDSCOPE from 2000 to 2004. We constrain our sample to this period because before 2000, dramatically less yearly data are available, and beginning in 2005, European companies had to adopt the International Financial Reporting Standards (IFRS). Extracted databases range from a total of 652 firm–year observations referring to 186 different firms in Italy to 5331 firm–year observations referring to 1305 firms in the UK (Table 1). All the variables are winsorised at 1% of each tail.

4. Estimation results

The descriptive statistics for the estimated models are presented in Tables 1 to 3. The number of firm–year observations for which it is possible to estimate AAs by alternative estimation approaches is shown in Table 1. As expected, the use of the conventional 2SICy approach significantly constrains the number of firm–year observations for which is possible to estimate

Table 1. Summary of estimation samples by approach and by country.

	Estimation Approach				
	SECTy	2SICy	SECTp	2SICp	MIX
France					
Number of firm–year observations	2277	2277	2277	2277	2277
Number of unique firms	649	649	649	649	649
Number of estimation samples	25	85	6	46	8
Number of observations per estimation sample (mean)	90	20	380	49	265
Number of abnormal accruals estimated	2256	1669	2277	2235	2146
Abnormal accruals estimated over potentially available observations	99.1%	73.3%	100%	98.2%	94.2%
Germany					
Number of firm–year observations	2310	2310	2310	2310	2310
Number of unique firms	662	662	662	662	662
Number of estimation samples	25	78	5	38	8
Number of observations per estimation sample (mean)	92	23	461	59	274
Number of abnormal accruals estimated	2303	1823	2303	2246	2163
Abnormal accruals estimated over potentially available observations	99.7%	78.9%	99.7%	97.2%	93.6%
Italy					
Number of firm–year observations	652	652	652	652	652
Number of unique firms	186	186	186	186	186
Number of estimation samples	20	26	5	26	7
Number of observations per estimation sample (mean)	31	11	129	24	93
Number of abnormal accruals estimated	626	283	647	611	584
Abnormal accruals estimated over potentially available observations	96%	43.4%	99.2%	93.7%	89.6%
United Kingdom					
Number of firm–year observations	5331	5331	5331	5331	5331
Number of unique firms	1305	1305	1305	1305	1305
Number of estimation samples	30	173	6	59	9
Number of observations per estimation sample (mean)	178	28	888	90	581
Number of abnormal accruals estimated	5326	4847	5326	5316	5054
Abnormal accruals estimated over potentially available observations	99.9%	90.9%	99.9%	99.7%	94.8%

Note: Estimation approaches and accruals models are defined in the text. All estimation samples with less than eight observations are excluded from the analysis.
Source: Authors.

AAs over the potentially available observations for all the countries. The approach commonly used for the US capital market (i.e., 2SICy) generates a high attrition of estimation samples for countries with smaller capital markets, while the three other industry-based estimation approaches preserve significantly more information. For instance, using the 2SICy approach for Italian data could eliminate more than half of any randomly selected study sample because 2SICy allows for the estimation of AAs for only 43% of the available observations.

All of the other industry-based estimation approaches (i.e., SECTy, SECTp, and SICp) allow researchers to use more than 90% of the available observations in all countries, eliminating the differences in the sample attrition between larger and smaller capital markets.

The MIX approach results in the second highest loss of available observations after the 2SICy approach, but it allows for the estimation of AAs using approximately 90% of the available observations in all the analysed countries. The loss of observations occurs because we decide to automatically exclude from the analysis the estimation sample with the highest standard deviation for any given accruals model. The rationale for this choice is that for all of the accruals models tested and countries analysed, there is usually one estimation sample identified by the MIX approach that has residuals with a standard deviation that is notably higher than the others. This result is consistent with the idea that the MIX approach identifies a residual group of firms with peculiar AGPs that differ significantly not only

Table 2. Standard deviations of abnormal accruals by estimation approach, country and accruals model.

	Estimation Approach				
Accruals Model	SECTy	2SICy	SECTp	2SICp	MIX
France					
Jones (1991)	0.105	0.102	0.110	0.104	0.078
Dechow et al. (1995)	0.106	0.103	0.111	0.105	0.080
Ball and Shivakumar (2006)	0.087	0.079	0.095	0.087	0.054
Modified Dechow and Dichev (2002)	0.086	0.076	0.093	0.084	0.052
Germany					
Jones (1991)	0.141	0.130	0.148	0.137	0.092
Dechow et al. (1995)	0.143	0.131	0.149	0.140	0.100
Ball and Shivakumar (2006)	0.130	0.113	0.139	0.124	0.074
Modified Dechow and Dichev (2002)	0.130	0.111	0.142	0.129	0.076
Italy					
Jones (1991)	0.067	0.052	0.078	0.067	0.047
Dechow et al. (1995)	0.069	0.057	0.080	0.070	0.055
Ball and Shivakumar (2006)	0.054	0.048	0.068	0.057	0.036
Modified Dechow and Dichev (2002)	0.056	0.036	0.074	0.059	0.036
UK					
Jones (1991)	0.142	0.127	0.146	0.136	0.111
Dechow et al. (1995)	0.142	0.128	0.146	0.137	0.088
Ball and Shivakumar (2006)	0.179	0.158	0.190	0.176	0.094
Modified Dechow and Dichev (2002)	0.179	0.156	0.188	0.177	0.096

Source: Authors.

Table 3. Estimation results for Jones (1991) model on UK data: 2SICy versus MIX estimation approach.

	Coefficient				p-value			
	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3
Panel A: 2SICy								
Intercept	−0.03	−0.07	−0.04	0.00	0.36	0.08	0.26	0.66
1/Total Assets	−122.94	−171.57	15.15	213.09	0.34	0.04	0.23	0.61
ΔREV	0.01	−0.07	0.01	0.10	0.33	0.05	0.21	0.61
PPE	−0.04	−0.10	−0.03	0.02	0.41	0.13	0.37	0.61
	R^2				Normality test: p-value			
	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3
	0.286	0.101	0.220	0.409	0.31	0.08	0.15	0.62
	Coefficient				p-value			
	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3
Panel B: MIX								
Intercept	−0.03	−0.05	−0.05	−0.02	0.01	0.00	0.00	0.00
1/Total Assets	−22.90	−28.34	−6.79	9.76	0.01	0.00	0.00	0.00
ΔREV	0.03	−0.06	0.03	0.12	0.01	0.00	0.00	0.00
PPE	−0.04	−0.08	−0.03	−0.01	0.18	0.00	0.00	0.19
	R^2				Normality test: p-value			
	Mean	Q1	Median	Q3	Mean	Q1	Median	Q3
	0.339	0.081	0.224	0.491	0.41	0.20	0.41	0.59

Source: Authors.

from those of the firms in other estimation samples but also from the firms in the same estimation sample. For this reason, we treat those observations as outliers, omitting them from the analysis. Table 2 shows that the heterogeneity of estimated AAs as measured by their standard deviation is typically reduced by cross-sectional approaches (2SICy and SECTy) relative to the pooled approaches (2SICp and SECTp), and this result suggests that AGPs are not usually stable over time within industries. Among the traditional estimation approaches, the 2SICy approach provides the lowest standard deviations regardless of the country and the accruals model, but the MIX approach always reduces heterogeneity to a

greater extent than 2SICy. Thus, our finding is that the MIX and 2SICy approaches allow for the estimation of relatively more uniform AAs than other approaches and are less inflated by the heterogeneity of AGPs.

Finally, it is worth noting that the MIX approach increases the explanatory power, the goodness of fit and the statistical significance of the models' coefficients in comparison with traditional estimation approaches. This trend is generally true for all of the accruals models tested and for all countries. To compare the estimation results from the most popular estimation approach (i.e., 2SICy) with those of the MIX approach in detail, we present the estimation of the Jones model using UK data (Table 3). The R-squared statistics computed over estimation samples are higher at the mean level and at each quartile for the MIX approach than for the 2SICy approach. We investigate the normality assumption through the Shapiro-Wilkinson test over the residuals of the estimated models, which are the measures of AAs within each estimation sample. Residuals from the MIX approach are non-normal more rarely than those of the SICy approach. The empirical distributions of estimated coefficients over estimation samples using the two different approaches are quite similar, but the statistical significance is always much higher for the coefficients estimated using MIX approach. Using the 2SICy approach, the change in the revenues variable (ΔREV) is not significant for more than half of the estimation samples, whereas using the MIX approach, ΔREV is always statistically significant. The difference in the statistical significance between the two estimation approaches is even higher for coefficients of the property, plant and equipment variable (PPE). This coefficient is properly estimated as being negative for over half of the estimation samples using the 2SICy approach, but it is seldom significant. Using MIX approach, it is estimated as being negative at each quartile and significantly negative at the first quartile and the median. Thus, our estimation results show that the MIX approach is able to improve the fit of accruals models relative to the widely used 2SICy approach and all other industry-based approaches, even if it identifies a lower number of estimation samples than traditional estimation approaches.

4.1. Insights on ex post economic interpretations of MIX estimation samples

Using a data-driven approach, such as the MIX approach, to identify estimation samples may result in clusters that are difficult to interpret because they might be groups of very different firms. For this reason, it is necessary to investigate whether there are possible *ex post* economic interpretations of MIX estimation samples. Moreover, the identification of the most relevant latent dimensions that generate the grouping provided by the MIX approach might suggest new criteria, other than industry classification, which may result in more homogenous estimation samples.

As a strategy to identify which variables mainly drive the grouping outcomes, we investigate whether and the degree to which the estimation samples identified by each combination of estimation approach/accruals model differ with respect to variables that prior research has proven to affect the AGP of firms and/or describe firm-specific relevant features. Specifically, we select the following four sets of variables on the basis of their popularity in the literature and relevance to our study: (1) accruals determinant variables such as the turnover of receivables, inventories and payables (Dechow, Kothari, & Watts, 1998; Dopuch et al., 2012; Kang & Sivaramakrishnan, 1995); (2) the Jones model's variables; (3) size variables (Ecker et al., 2013; Kothari et al., 2005; Watts & Zimmerman, 1978); and (4) other variables that

are usually used as control variables in earnings management and earnings quality studies, such as leverage, operating cash flows and return ratios (Francis & Wang, 2008). For each of these variables, we perform a non-parametric ANOVA, testing the null hypothesis that the median levels over the estimation samples of any given combination of estimation approach/accruals model are equal. A rejection implies that the variable significantly describes the grouping outcome. The stronger the rejection, the more the variable discriminates among estimation samples.

Table 4 shows the values of the statistical tests for differences in median between the estimation samples identified by the two-digit SIC code-based estimation approaches (i.e., 2SICy and 2SICp) and the MIX approach (for each of the four accruals models) for the UK sample. For each combination of estimation approach/accruals model, the first column presents the values of the test statistics for each variable, and the second column lists the rank in descending order of the value of the test with respect to the test values of the other variables for the same combination of estimation approach/accruals model. We rank the values of the test to identify the set of variables according to which the estimation samples for any combination of estimation approach/accruals model differ to a greater extent. In Table 4, the top five ranked variables are highlighted. In the UK sample, the two-digit SIC code-based estimation approaches (i.e., 2SICp and 2SICy) identify estimation samples that are primarily characterised by different median values of the accruals determinant variables. Given the strong theoretical relationship between these variables and the AGP of a firm (Kang & Sivaramakrishnan, 1995; Dechow et al., 1998; Kang & Sivaramakrishnan, 1995), our results support the use of the two-digit SIC code estimation approaches. The MIX approach identifies estimation samples that appear to be distinguished primarily by differences in size. The test values of at least two of the four book size variables selected (i.e., total assets, lagged total assets, revenues, lagged revenues) range from the second to the fifth rank in all four accruals models. The relationship between the firm's size and accruals, although not theoretically founded, is well-documented, as several firm characteristics that affect AGP, such as growth, diversification and monitoring, are correlated with size (Ecker et al., 2013).

5. Simulation results

The average empirical rejection frequencies from 1000 simulations when no observations in the randomly selected study samples are manipulated (untabulated) are quite close to the expected level of 5%. Thus, all the accruals models analysed appear to be always well-specified.

Table 5 presents the probabilities of detecting earnings management activity when the reported earnings of five observations, randomly selected within a study sample of 100 firm–year observations, have been manipulated through an expense manipulation for all four countries. Our simulation results confirm the limited probability of discovering artificially induced manipulations of small but economically material magnitude. When the amount of the manipulation increases, however, this probability also increases following different trajectories. The main drivers of these different patterns are: (1) different estimation approaches; (2) different accruals models; and (3) different countries.

Regarding traditional industry-based estimation approaches, the two cross-sectional approaches by year and industry (i.e., SECTy and 2SICy) tend to provide more powerful tests for earnings management than their counterparts that pool firm observations across

Table 4. Test statistics of non-parametric ANOVA and rank in descending order by combination of estimation approach/accruals model for the UK.

	Combination of Estimation Approach/Accruals Model											
	SIC2p		SIC2y		MIX		MIX		MIX		MIX	
	Model (J)		Model (J)		Model (J)		Model (DSS)		Model (BS)		Model (MDD)	
Variable	Test	Rank	Test	Rank	Test	Rank	Test	Rank	Test	Rank	Test	Rank
Accruals determinants												
Receivables Turnover	1619	4	1410	4	154	17	108	18	285	15	317	14
Payables Turnover	754	12	575	11	133	18	204	16	159	18	242	17
Inventory Turnover	1935	2	1736	1	273	14	185	17	204	17	90	19
Operating Cycle	1325	6	1199	6	481	9	430	10	352	12	250	16
Dep-to-PPE ratio	2021	1	1747	2	808	4	820	3	671	2	573	9
Jones model's variables												
TA_ind	378	18	440	16	913	1	896	1	422	11	363	12
TA_dir	380	17	480	15	583	7	526	8	725	1	727	4
ΔREV	241	19	400	17	83	19	39	19	81	19	163	18
PPE	1723	3	1542	3	410	10	447	9	341	13	413	11
Size variables												
Total Assets	995	9	866	9	843	3	786	4	624	3	766	3
Total Assets_lagged	983	10	848	10	886	2	825	2	580	8	717	5
Revenues	1078	8	884	7	713	6	707	6	613	4	707	6
Revenues_lagged	1088	7	882	8	723	5	730	5	599	6	706	7
Mrk_Cap	729	13	665	12	579	8	542	7	476	10	547	10
Other relevant variables												
Leverage	784	11	759	18	298	13	309	12	216	16	280	15
CashFlow	471	16	417	19	366	11	301	13	611	5	608	8
ΔCashFlow	40	20	259	20	17	20	10	20	5	20	15	20
PPEn-to-PPEg ratio	1550	5	1476	5	238	16	279	15	296	14	361	13
ROA	485	15	588	14	266	15	290	14	587	7	1218	1
ROI	520	14	559	13	301	12	341	11	495	9	948	2
No. of Estimation Samples	58		172		7		7		7		9	

Source: Authors.

years (i.e., SECTp and 2SICp). In addition, the approaches based on two-digit SIC codes (i.e., 2SICp and 2SICy) tend to provide higher probabilities to detect earnings management than those based on sectors (i.e., SECTp and SECTy). Therefore, the finer the industry classification, the higher the probability of discovering earnings manipulations, but the smaller the number of potentially available observations in small capital market countries. In summary, the 2SICy approach provides the most powerful tests among the industry-based estimation approaches for all the accruals models and in all the countries analysed.

The MIX approach significantly improves the probability of detecting earnings manipulations in nearly all combinations of accruals models and amounts of manipulation, with very few, and no statistically significant, exceptions.

To determine if these results are driven by the specific industry classifications selected (i.e., two-digit SIC code and sector), we repeat the simulation on UK data alone using the Jones model estimated cross-sectionally by year and two further alternative industry classifications. Specifically, we replace the 81 two-digit SIC codes with Fama and French's (1997) 48 industries and the 25 two-digit Datastream industry groups. The untabulated results do not reveal any substantial contradictions of the previous findings: the finer the industry classification, the higher the probability of detecting earnings manipulations.

The second source of heterogeneity in the earnings manipulations detection probabilities arises from the choice of the accruals model. Our results suggest that there is no accruals

Table 5. Rejection frequencies based on one-tailed t-statistics for the null hypothesis of no earnings management ($\delta=0$) in presence of artificially induced earnings manipulations (expense manipulation), by estimation approach, country and accruals model.

Amount of manipulation	France Estimation Approach					Germany Estimation Approach					Italy Estimation Approach					United Kingdom Estimation Approach				
	SECTy	2SICy	SECTp	2SICp	MIX	SECTy	2SICy	SECTp	2SICp	MIX	SECTy	2SICy	SECTp	2SICp	MIX	SECTy	2SICy	SECTp	2SICp	MIX
Jones (1991) Model																				
1% of lagged total assets	0.070[c]	0.087	0.088	0.091	0.100	**0.070**	0.060	**0.076**	**0.073**	0.069	0.091[c]	0.089[c]	0.098[c]	0.089[c]	0.137	0.059[b]	**0.086**	0.057[c]	0.055[c]	0.084
2%	0.092[c]	0.120[b]	0.110[c]	0.131	0.150	0.092[a]	0.081[b]	0.097	0.093	0.110	0.164[c]	0.192[c]	0.153[c]	0.160[c]	0.258	0.082[c]	0.112[a]	0.078[c]	0.077[c]	0.131
3%	0.133[c]	0.153[c]	0.149[c]	0.165[c]	0.222	0.118[c]	0.113[c]	0.127[b]	0.121[c]	0.160	0.257[c]	0.357[c]	0.219[c]	0.237[c]	0.414	0.104[c]	0.143[c]	0.103[c]	0.106[c]	0.184
4%	0.174[c]	0.202[c]	0.193[c]	0.213[c]	0.328	0.147[c]	0.147[c]	0.152[c]	0.152[c]	0.227	0.378[c]	0.546[c]	0.305[c]	0.355[c]	0.599	0.131[c]	0.172[c]	0.127[c]	0.141[c]	0.263
5%	0.229[c]	0.282[c]	0.257[c]	0.276[c]	0.441	0.186[c]	0.195[c]	0.181[c]	0.204[c]	0.302	0.516[c]	0.700[c]	0.407[c]	0.484[c]	0.764	0.176[c]	0.215[c]	0.155[c]	0.188[c]	0.366
Dechow et al. (1995) Model																				
1% of lagged total assets	0.065[b]	0.090	0.079	0.086	0.091	0.066	0.066	**0.079**	0.068	0.070	0.085	**0.096**	**0.100**	0.089	0.091	0.066	**0.090**	0.062	0.061	0.073
2%	0.092[c]	0.118[c]	0.107[b]	0.125[c]	0.152	0.089	0.081[b]	0.093	0.089	0.103	0.151[b]	**0.193**	0.150[b]	0.155[b]	0.187	0.084[a]	**0.117**	0.081[a]	0.082[a]	0.102
3%	0.130[c]	0.149[c]	0.150[c]	0.166[c]	0.220	0.120[c]	0.116[c]	0.118[c]	0.111[c]	0.164	0.251[c]	**0.313**	0.207[c]	0.229[c]	0.305	0.105[c]	0.139	0.105[c]	0.105[c]	0.158
4%	0.181[c]	0.206[c]	0.195[c]	0.211[c]	0.306	0.146[c]	0.151[c]	0.147[c]	0.143[c]	0.224	0.366[c]	**0.472**	0.290[c]	0.334[c]	0.447	0.131[c]	0.175[c]	0.130[c]	0.144[c]	0.225
5%	0.226[c]	0.278[c]	0.254[c]	0.276[c]	0.430	0.179[c]	0.193[c]	0.177[c]	0.186[c]	0.297	0.498[c]	0.637	0.393[c]	0.454[c]	0.639	0.174[c]	0.214[c]	0.157[c]	0.195[c]	0.322
Ball and Shivakumar (2006) Model																				
1% of lagged total assets	0.079[b]	0.074[c]	0.074[b]	0.065[c]	0.109	0.074	0.062[b]	0.066[b]	0.071[a]	0.088	0.102[a]	**0.142**	0.108	0.097[a]	0.122	0.047[b]	**0.065**	0.043[b]	0.045[b]	0.065
2%	0.119[c]	0.130[c]	0.116[c]	0.114[c]	0.187	0.094[c]	0.101[c]	0.083[c]	0.086[c]	0.138	0.202[c]	**0.343**	0.162[c]	0.179[c]	0.327	0.060[c]	0.084	0.050[c]	0.054[c]	0.097
3%	0.166[c]	0.198[c]	0.162[c]	0.183[c]	0.310	0.123[c]	0.142[c]	0.121[c]	0.117[c]	0.212	0.332[c]	**0.606**	0.217[c]	0.298[c]	0.599	0.078[c]	0.105[c]	0.068[c]	0.065[c]	0.143
4%	0.246[c]	0.325[c]	0.223[c]	0.253[c]	0.499	0.162[c]	0.180[c]	0.162[c]	0.155[c]	0.319	0.474[c]	**0.810**	0.313[c]	0.444[c]	0.786	0.098[c]	0.128[c]	0.086[c]	0.092[c]	0.213
5%	0.357[c]	0.440[c]	0.325[c]	0.379[c]	0.672	0.203[c]	0.245[c]	0.191[c]	0.195[c]	0.438	0.649[c]	**0.923**	0.436[c]	0.605[c]	0.904	0.124[c]	0.164[c]	0.108[c]	0.119[c]	0.293
Modified Dechow and Dichev (2002) Model																				
1% of lagged total assets	0.056[b]	0.073[a]	0.070[b]	0.071[b]	0.092	0.070	0.068	0.066	0.075	0.072	0.091[c]	**0.123[a]**	0.085[c]	0.091[c]	0.145	0.052[c]	0.058	0.042[c]	0.042[c]	0.086
2%	0.104[c]	0.114[c]	0.107[c]	0.108[c]	0.181	0.088[c]	0.088[c]	0.088[c]	0.098[b]	0.122	0.191[c]	0.240[c]	0.154[c]	0.169[c]	0.345	0.058[c]	0.076[c]	0.050[c]	0.061[c]	0.117
3%	0.159[c]	0.200[c]	0.150[c]	0.166[c]	0.347	0.114[c]	0.125[c]	0.109[c]	0.131[c]	0.191	0.350[c]	0.415[c]	0.241[c]	0.312[c]	0.607	0.086[c]	0.104[c]	0.062[c]	0.073[c]	0.171
4%	0.244[c]	0.308[c]	0.229[c]	0.251[c]	0.522	0.147[c]	0.174[c]	0.142[c]	0.166[c]	0.310	0.521[c]	0.607[c]	0.382[c]	0.486[c]	0.828	0.109[c]	0.137[c]	0.077[c]	0.092[c]	0.227
5%	0.350[c]	0.441[c]	0.306[c]	0.349[c]	0.705	0.193[c]	0.241[c]	0.175[c]	0.213[c]	0.439	0.667[c]	0.771[c]	0.522[c]	0.659[c]	0.937	0.134[c]	0.173[c]	0.102[c]	0.110[c]	0.315

Notes: [a,b,c]Significantly different from the equivalent MIX power at 10%, 5%, and 1% respectively using a one-tailed binomial test.
In bold powers of industry based approaches equal to or higher than those provided by MIX.
Source: Authors.

Table 6. Rejection frequencies based on one-tailed t-statistics for the null hypothesis of no earnings management ($\delta=0$) in presence of artificially induced earnings manipulations, for the Jones (1991) model based tests on UK data, by different size of study sample, different percentage of manipulated observations within the study sample, and estimation approach.

Amount of Manipulation	5% of Obs. Manipulated Estimation Approach					10% of Obs. Manipulated Estimation Approach					20% of Obs. Manipulated Estimation Approach				
	SECTy	2SICy	SECTp	2SICp	MIX	SECTy	2SICy	SECTp	2SICp	MIX	SECTy	2SICy	SECTp	2SICp	MIX
Study Sample of 100 firm–year Obs.															
1% of lagged total assets	0.059	0.086	0.057	0.055	0.084	0.082	0.080	0.080	0.082	0.095	0.077	0.097	0.083	0.099	0.119
2%	0.082	0.112	0.078	0.077	0.131	0.115	0.139	0.118	0.110	0.166	0.153	0.165	0.146	0.157	0.263
3%	0.104	0.143	0.103	0.106	0.184	0.172	0.205	0.171	0.174	0.283	0.225	0.269	0.230	0.221	0.419
4%	0.131	0.172	0.127	0.141	0.263	0.241	0.268	0.231	0.239	0.434	0.323	0.362	0.313	0.337	0.613
5%	0.176	0.215	0.155	0.188	0.366	0.310	0.359	0.297	0.327	0.563	0.440	0.482	0.405	0.438	0.764
Study Sample of 500 firm–year Obs.															
1% of lagged total assets	0.094	0.097	0.089	0.104	0.138	0.139	0.140	0.123	0.149	0.207	0.139	0.192	0.134	0.178	0.280
2%	0.160	0.190	0.155	0.179	0.314	0.257	0.308	0.240	0.284	0.513	0.339	0.422	0.336	0.391	0.682
3%	0.264	0.298	0.257	0.290	0.528	0.423	0.497	0.413	0.460	0.783	0.594	0.675	0.571	0.634	0.934
4%	0.408	0.453	0.397	0.427	0.740	0.617	0.699	0.621	0.649	0.936	0.801	0.878	0.781	0.829	0.995
5%	0.553	0.602	0.531	0.566	0.885	0.774	0.849	0.758	0.790	0.983	0.937	0.965	0.918	0.957	0.999
Study Sample of 1000 firm–year Obs.															
1% of lagged total assets	0.108	0.135	0.112	0.112	0.223	0.175	0.191	0.163	0.164	0.299	0.225	0.244	0.226	0.239	0.456
2%	0.242	0.304	0.229	0.250	0.515	0.392	0.446	0.368	0.388	0.716	0.557	0.634	0.515	0.587	0.923
3%	0.426	0.526	0.413	0.442	0.806	0.644	0.708	0.632	0.675	0.955	0.847	0.913	0.840	0.873	0.997
4%	0.606	0.726	0.600	0.628	0.944	0.855	0.903	0.827	0.872	0.997	0.974	0.988	0.961	0.975	1.000
5%	0.771	0.875	0.760	0.795	0.990	0.953	0.978	0.951	0.973	1.000	0.995	1.000	0.993	0.957	1.000

Note: The table shows the result of the following simulation processes. 100, 500 and 1000 firm–year observations, for which abnormal accruals have been estimated using the Jones (1991) model and the specified estimation approach, are selected without replacement respectively, and then a dummy variable (PART) that equals one for 5, 10, and 20%, respectively, of the selected observations and zero for the others is created. The earnings of the firm–year observation for which PART=1 are artificially manipulated by adding the assumed amount to the total accruals (i.e., expense manipulation).

Source: Authors.

model that definitively outperforms the others in all the countries analysed. On one hand, Ball and Shivakumar (2006) accruals model and the modified version of the model proposed by Dechow and Dichev (2002) seem to provide the most powerful tests for earnings management in the continental countries France, Germany and Italy, regardless of the estimation approach employed. On the other hand, in the UK, the Jones (1991) and the Dechow et al. (1995) models appear to better detect earnings manipulations than the other two accruals models.

The comparisons of test powers for earnings management among countries reveal further differences that may be somewhat counterintuitive. Table 5 provides evidence of a negative correlation between the size of the original data set (which depend on the capital market size) and the ability to discover earnings manipulations. The sizes of the study samples are kept fixed using the rationale of neutralising the effect of study sample size on the power of tests. In a following step of our analysis, we increase the sizes of the study samples and the percentages of manipulated observations within them. Table 6 presents the results for the UK data using the Jones model and simulating an expense manipulation, but the findings are similar across all of the accruals models, types of earnings manipulations and countries analysed. The probability of detecting earnings manipulations appears to be an increasing function of the study sample size and the percentage of manipulated observations within the study sample.

It is worth noting that the probabilities of detecting earnings manipulation in the UK using a study sample of 1000 observations representing 93% of the average annual available observations are on average higher than those in Italy estimated using a study sample of 100 observations that represents the 77% of the average annual available observations. Thus, part of the difference in the detection probabilities across countries is explained by the size and coverage of the study sample, but a remaining component seems to be caused by the idiosyncratic features of each country. For instance, differences in earnings manipulations detection probabilities between France and Germany are consistently found to be significant, even if the two countries have approximately the same number of available observations. One possible explanation for this difference may be the coexistence of three different accounting regimes in Germany during the period studied here.

6. Conclusion

This study aims to assess how the estimation approach, and in particular the industry classification, affects the ability to discover earnings management activity in four European countries characterised by differences in the size of capital markets and the levels of sample attrition (namely, France, Germany, Italy, and the UK). Moreover, we consider an estimation approach based on a data-driven statistical procedure through the specification of a mixture model (MIX approach) that does not rely on any industry classification. By construction, the MIX approach optimises the fit to the data by jointly clustering firm–year observations in a number of estimation samples that is not fixed a priori and estimating the specified accruals model within each estimation sample.

The simulation results show that enlarging the industry classification from two-digit SIC codes and/or pooling observations across years hampers the ability to discover earnings management, even though those estimation approaches allow for an enlargement in the number of firm–year observations for which AAs can be estimated. However, we have also

observed that the larger the number of observations within the study sample, the greater the ability to discover earnings manipulations. Thus, when using traditional, industry-based estimation approaches in small capital market countries, a researcher must select the width of the industry classification, balancing the negative effect on the ability to detect earning manipulations produced by a wider industry classification with its positive effect on the coverage of the data set to optimise the probability of detecting earnings management activity in the specific research setting. The MIX approach seems to overcome this trade-off, allowing researchers to estimate AAs for more than 90% of available observations not only without reducing ability to identify earnings manipulations, but also increasing it in most cases. The MIX approach provides the highest probabilities to detect earnings management in all countries. Regarding the differences among countries, we find that no accruals model outperforms the others in every research setting. In continental European countries, the models incorporating the asymmetric timely recognition of gains and losses seem to perform better, whereas in the UK, the original Jones model and its most popular modified version (Dechow et al., 1995) appear to be more powerful. This study provides evidence that the estimation approach is a key choice in the 'total accrual' research design and shows that finding alternative criteria or techniques for identifying the estimation samples, such as size variables, may substantially improve the ability to detect earnings manipulations.

The study focuses on the largest capital markets in Europe, that is the ones for which the number of available firm-observations allows the comparison of the proposed industry-based estimation approaches. Nevertheless, our results are also relevant for the other European countries that have even fewer available observations than those analysed.

Notes

1. A notable exception is the study by Ecker, Francis, Olsson, and Schipper (2013).
2. We test also other two types of earnings manipulations (i.e., bad debt manipulation and revenue manipulation) and the results are qualitatively the same.
3. A real world example of expense manipulation that results in an accounting fraud can be retrieved in one of the largest accounting scandal of the last century: the WorldCom bankruptcy (Knowledge@Wharton, What Went Wrong at WorldCom?, 3 July 2002, available at: http://knowledge.wharton.upenn.edu/article/what-went-wrong-at-worldcom/)

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