IRMBR
www.irmbrjournal.com September 2014
International Review of Management and Business Research Vol. 3 Issue.3

Drivers of Hidden Reserves – Consequences for the Comparability of Financial Statements Under IFRS

GERNOT BRÄHLER
Professor, Head of Chair, Department of Business Taxation and Auditing
Ilmenau University of Technology, Germany
Email: gernot.braehler@tu-ilmenau.de
Tel: +49 3677 69-4498

SEBASTIAN SCHMIDT
PhD Candidate, Department of Business Taxation and Auditing
Ilmenau University of Technology, Germany
Email: sebastian.schmidt@tu-ilmenau.de
Tel: +49 841 3799964

Abstract

The comparability of IFRS financial statements is frequently discussed in literature and numerous researches show that entities from different countries or with particular characteristics tend to use IFRS differently. However, hidden reserves, i.e. the discrepancy between the historical book values and their fair value counterparts, are usually not part of these investigations. Since we assume that hidden reserves can be a reliable measure of comparability, the purpose of this paper is to examine if specific factors of a company like size, country of origin or industry membership also indicate different odds to observe hidden reserves. Analysing 456 purchase price allocations, we do indeed find evidence for our aforementioned assumption. Our results show that the probability to observe hidden reserves under IFRS seems to be dependent on certain factors. For instance, our results clearly indicate that large companies show hidden reserves more frequently than small companies. We also find that entities from particular countries exhibit significantly higher odds to hold hidden reserves than others. In consequence, we assume that the comparability of financial statements under IFRS is still not achieved.

Key Words: *Hidden Reserves, Comparability, Faithfulness, Financial Statements, IFRS, IFRS 3*.

Introduction

The faithfulness and comparability of financial statements is frequently discussed in literature. In this context, there are many different points of views examining the topic of comparability in particular. While some researchers focus on differences in the application of IFRS accounting principles between countries (e.g. Cole, Branson, & Breesch, 2013; Kvaal, & Nobes, 2012 or Ball, 2006), others look for differences between industries (e.g. Jafaar, &McLeay, 2007) or size (e.g. Nobes, & Perramon, 2013). There are also discussions about the usage of fair value accounting vs. historical cost accounting in IFRS and if one of these approaches is superior to provide comparable financial statements (e.g. Penman, 2007).

Without doubt, all these studies give useful insights to the comparability of the application of IFRS accounting principles. Nevertheless, these studies have also in common that they do not show the quantitative degree of comparability or rather incomparability. To be more precise, they do not measure the consequences of incomparable balance sheet figures under IFRS. A possible measure of comparability in this context would be the hidden reserves contained in financial statements. Hidden reserves can be defined as the discrepancy between the historical book values of balance sheet items and their fair value counterparts. This discrepancy can be caused by different reasons – like accounting choices or judgement options managers have by applying IFRS (e.g. stating property, plant and equipment at historical costs instead of fair value or determining the probable amount of provisions). In consequence, this means that a perfect comparability of financial statements could only be accomplished if hidden reserves did not exist.

In a study of Brähler and Schmidt (2014), hidden reserves under IFRS are empirically measured for the first time in detail. The paper describes the total amounts and the frequency of hidden reserves observed in financial statements. The study provides data for different countries and industries and shows that hidden reserves can reach high amounts and occur frequently. However, the results are presented only in a descriptive manner without any further explanation of the factors which can be seen as drivers of hidden reserves. Accordingly, it is not possible to differentiate if some countries or industries show significant higher amounts of hidden reserves than others.

The purpose of this paper is to fill this gap and link the aforementioned hidden-reserves-data to other related research in this field. If factors like country of origin, industry membership and size of an entity influence the application of IFRS accounting principles, then we must assume that these factors have also an impact on the probability that a company holds hidden reserves. Therefore, we use the descriptive data of Brähler and Schmidt (2014) to identify potential drivers of hidden reserves by performing a logistic regression. As a result, our investigation will provide additional empirical evidence if comparability under IFRS is achieved and which determinants indicate the existence of hidden reserves in the case of a specific entity.

The remainder of this paper is organized as follows: Related literature is reviewed in the next section. Section 3 provides background information on the data we used and contains some preliminary considerations to our research design. We formulate our hypotheses in section 4 and describe our methodology for testing them in section 5. Our findings and results are outlined in section 6. At last, Section 7 contains our conclusions.

Literature Review

Our study is basically related to research in the fields of hidden reserves and the comparability of financial statements under IFRS.

In this context, most examinations deal directly with the comparability of financial reports or indirectly with the harmonization process of accounting practices under IFRS. Most research is focusing on factors that influence comparability. Some of these studies reveal that companies are sticking to their pre-IFRS national accounting practices where this is allowed within IFRS (Haller, & Wehrfritz, 2013; Kvaal, & Nobes, 2012 and 2010; Nobes, 2013 and 2011). Cole, Branson, & Breesch (2013) have also conducted research in this field. Their findings indicate that factors like country of origin, industry and the type of auditor have a strong influence on how accounting choices are used in practice. In contrast, factors like the size of a company or its capital structure seem to have no relevance for accounting choices. However, relating to firm size, Nobes and Perramon (2013) come to a different conclusion. Their research shows that the size of a company does influence accounting practices.

Further examinations deal with the harmonization process of accounting principles. Liao, Sellhorn and Skaife (2012) investigate a sample of French and German entities. They indicate that earnings and book values are comparable in the year subsequent to IFRS adoption, but become less comparable in the years that follow. An investigation of Callao, Ferrer, Jarne and José (2009) observes the impact of IFRS on the financial reporting of European countries. They also use their data to measure if companies from different countries can still be divided into the Anglo-Saxon or continental-European accounting systems. The study comes to the conclusion that, while differences between countries still exist, the traditional classification of countries into either the Anglo-Saxon or the continental-European group not exists anymore.

Salter, Kang, Gotti and Doupnik (2013) examine whether societal values can explain differences in levels of accounting conservatism across countries. They find that conservatism is greater in countries with more conservative societal and accounting values. In summary, basically all studies show that comparability or harmonization is currently not achieved under IFRS and that a wide range of factors exists that seem to explain these differences.

There are rarely investigations that refer to the topic of hidden reserves directly, and usually they do not examine hidden reserves explicitly as a measure to assess the level of comparability and reliability of financial reports. However, the study of Brähler and Schmidt (2014) reveals at least the frequency of the occurrence of hidden reserves in entities from different countries and industries, which balance sheet items mainly comprise hidden reserves and to what numbers they amount.

In addition, a study that uses hidden reserves is conducted by Rodríguez-Pérez, Slof, Solà, Torrent and Vilardell (2011). They investigate the impact of fair value accounting on financial statements by applying a data envelopment analysis (DEA) to compare the efficiency and profitability of different companies. In this context, they provide an overview of the hidden reserves they have revealed in their study. Nevertheless, the hidden reserves shown are based on Spanish-GAAP and limited to the positions of financial investments as well as land and buildings.

Data and Preliminary Considerations

For our investigation we use the hand collected data by Brähler and Schmidt (2014). We find this data appropriate to measure hidden reserves since it is based on IFRS 3 Purchase Price Allocations (PPAs). This background is important because of two reasons:

First, the applied PPAs allow an exact measurement of hidden reserves because of the requirements of IFRS 3. According to IFRS 3 in the version of 2004, assets and liabilities are stated in both historical book values and fair values; therefore, hidden reserves can be deduced accurately as the difference between these two sets of values.

Second, the fair values disclosed in a purchase price allocation can be seen as reliable. This fact is essential, since the measurement of fair value is frequently criticised in literature because it is often difficult to observe market prices or similar standards of comparison to determine the "true" fair value (Cole, Branson, & Breesch, 2011; Martin, Rich, & Wilks, 2006; Penman, 2007; Watts, 2006; Whittington, 2008). In the case of a PPA this problem does not exist, since all fair values are definitely determined and stipulated by independent and different parties in a purchase process.

In a next step, we reviewed the available data of Brähler and Schmidt (2014) to evaluate which hypotheses could probably be investigated with the dataset and which statistical methods would be appropriate for that. The original dataset consists of 456 PPAs and provides different sub-samples with each sub-sample reflecting frequency and amounts of hidden reserves for a specific balance sheet item (e.g. property, plant and equipment, long-term investments, inventories, provisions). The data also contains information about the industry and country of origin of the observed entity. In some sub-samples, there are also additional details given; for instance, the applied cost method to measure inventories or the applied useful lives (depreciation rate) of the PPE. The depreciation rates are shown as a range for the parts of buildings and other PPE. However, the PPE observations themselves are not itemised. Accordingly, the use of this variable is restricted. We will further discuss this topic in our results.

Moreover, the sub-samples comprise different numbers of observations. In many cases the number of observations is insufficient for a proper analysis with statistical methods. Therefore, we focus only on the sub-samples PPE and inventories. In comparison to the other sub-samples these items offer simultaneously the most observations in total and a sufficient number of observations for each of the dependent variables.

To allow a more detailed research, we additionally extended the existing data by collecting further information, in particular on the size of the observed entities, their turnover (to calculate balance sheet ratios) and the year they were acquired. In this context, size was measured as the amount of the total balance sheet assets.

Usually we were able to gather the additional data from the related PPAs published in the financial reports of the acquirer. However, in some cases we had to complete missing information with the help of databases like Thomson Reuters Worldscope, Bloomberg or, rarely, press releases. Nevertheless, we could not get the required data for all observations. To sum up, we got 23% missing values for the variable turnover, 7% to 9% for the depreciation rates of PPE and 6% regarding the measurement methods of the inventories. To avoid considerably smaller sub-samples by eliminating observations with missing values, we use multiple imputation to complete our datasets. We choose this approach because in comparison to other methods, multiple imputation probably offers the best estimates to handle missing data (cf. Graham, & Schafer, 2002; Ibrahim, Chen, Lipsitz, & Herring, 2005).

The process of multiple imputation works basically by developing a regression model to predict observed values of a variable based on other variables. This model is then used to estimate the missing values. In the case of multiple imputation this process is done several times for each missing variable. As a result, there are different imputed datasets without missing values that can be analysed separately. The different results can then be summarized and evaluated as a whole. In our investigation, we calculated 10 imputation models. A higher number of models did not display any substantially different results. At this point we have to state that the multiple imputation demands certain requirements on the dataset that are tested by a missing value analysis. In our case, all requirements to perform a multiple imputation are met. Therefore, we finally receive two complemented datasets for the sub-samples of PPE (398 observations) and inventories (281 observations).

Development of Hypotheses

1. Country of Origin: Previous research shows that entities from different countries tend to stick to their pre-IFRS accounting practices (Haller, & Wehrfritz, 2013; Kvaal, &Nobes, 2012 and 2010; Nobes, 2013 and 2011). Furthermore, other studies imply that conservative accounting supports the emergence of hidden reserves (Hellman, 2008; Penman, & Zhang, 2002). Since conservatism is usually a phenomenon of code-law-countries (Lara, & Mora, 2004), we formulate hypothesis H1a:

H1a: *Entities in code-law-countries are more likely to show hidden reserves than entities from common-law-countries.*

Additionally, the prudence principle is more relevant in code-law-countries. Therefore, we analogically postulate that hidden burdens are less likely to occur in these countries:

H1b: *Entities in code-law-countries are less likely to show hidden burdens than entities from common-law-countries.*

2. Industry and Size: Besides country-effects, other factors can also influence the practical application of accounting principles (Cole, Branson, &Breesch, 2013; Nobes, 2013; Watts, 1992; Watts, &Zimmermann, 1990). More specific, the factors industry (Jaafar, & McLeay, 2007) and size (Nobes, & Perramon, 2013) seem to be relevant. In the case of the size of an entity, we suppose that especially large companies tend to show hidden reserves or burdens more frequently. This assumption is based on two facts: first, large companies own more assets that can potentially hold hidden reserves or burdens and second, existing research indicates that large entities try to avoid fair value measurement more frequently than smaller companies because of higher political costs (Quagli, & Avallone, 2010). Therefore, we determine hypotheses H2 and H3:

H2: *The likelihood to show hidden reserves and burdens varies between entities from different industries.*

H3: *Large entities are more likely to show hidden reserves or burdens than small companies.*

3. Financial Ratios: We also control for particular financial ratios, since we assume that those ratios may indicate the probability to observe hidden reserves as well. We focus on ratios that measure the relation of an asset to the turnover of an entity. In the case of PPE this will be the variable PPEOT (PPE on Turnover = PPE / Turnover) and in the case of inventories the variable IOT (Inventories on Turnover = Inventories / Turnover). A low ratio of these terms indicates that the business has less money tied up in assets for each unit of revenues it receives. Keeping this in mind, we additionally suppose that hidden reserves can also be seen as hidden capacities, e.g. if a machine is already fully depreciated but still functioning and part of the production process. Therefore, we assume that between two entities with equal turnover the entity with the lower ratios is more likely to show hidden reserves because it has more likely hidden capacities to earn the additional revenues.

H4: *The lower the PPEOT, the higher the likelihood that an entity shows hidden reserves.*

H5: *The lower the IOT, the higher the likelihood that an entity shows hidden reserves.*

Moreover, we also include the variable DR (Debt Ratio = Debt / Total Balance Sheet Assets) in our model. Since entities need the capital markets to finance their operations, companies with high debts might try to enhance their balance sheet figures by applying accounting policies in such a way as to avoid hidden reserves. Therefore, the entity can show higher asset values covering their debts. Analogically, entities with a high DR might also tolerate hidden burdens to show not even higher debts in their balance sheets.

H6a: *The lower the DR, the higher the likelihood that an entity shows hidden reserves.*

H6b: *The higher the DR, the higher the likelihood that an entity shows hidden burdens.*

4. Measurement Methods: The depreciation rates for PPE can influence the emergence of hidden reserves or burdens directly. While a depreciation rate that is shorter than the actual useful life will likely lead to hidden reserves, a longer rate will probably support the generation of hidden burdens.

H7a: *The shorter the depreciation rate, the higher the likelihood that an entity shows hidden reserves.*
H7b: *The longer the depreciation rate, the higher the likelihood that an entity shows hidden burdens.*

In the case of inventories, we assume that the FIFO method measures inventories closer to the current market value than other approaches like e.g. the weighted average method. Accordingly, we suspect entities using FIFO to show less hidden reserves or burdens.

H8: *Entities that do not use FIFO are more likely to show hidden reserves or burdens.*

5. Year: At last we include the year of the PPA into our model. This variable is used as a control variable to determine whether particular events that might have happened during a year influence the occurrence of hidden reserves, e.g. effects of the financial crisis.

Research Design

To control our hypotheses we use a multinomial logistic regression model (MLR). We choose this approach because it seems to be the most adequate method for the given data and the purpose of this investigation.

As far as the level of measurement is concerned, the hidden reserves (dependent variable) are measured on a metric scale, whereas most other (independent) variables are measured on a nominal or ordinal scale. These characteristics of the data influence the possible statistical methods which can be used in this investigation. Initially, the metric scale level of hidden reserves would imply the application of a linear regression. However, most independent variables like country and industry are on a nominal level.

A regression model seems not appropriate in this case, since the usage of numerous nominal dummy-variables complicates the interpretation of the results. Due to the fact that most independent variables must be seen as endogenous, another problem arises. Variables like the DR or the country of an entity are only proxies for the actual causes of hidden reserves.

These actual causes consist of judgement options and accounting choices that managers may typically make in a particular environment, determined by the industry, the country or other factors of an entity. Accordingly, there is no linear relationship between the dependent and the independent variables, which is why a linear regression approach provides no sufficient results in this case. Moreover, the exact amount of hidden reserves and burdens is not that important for the purpose of this investigation, since we are rather interested in their occurrence. As a consequence, it is favourable to use MLR.

Therefore, we treat the variable of hidden reserves as a categorical variable that can fall into three different outcome categories: no hidden reserves or burdens occurred (y=0), hidden reserves occurred (y=1) or hidden burdens occurred (y=2).

In principle, the approach of MLR works by comparing the probability of belonging to each of the n-1 categories compared to a baseline or reference category. In our model, the reference category is y=0 (no reserves or burdens occurred). Following Fienberg, 1977 and Hosmer and Lemeshow, 2000, the formula for MLR can be described as:

$$P(y_i = j) = \frac{\exp(x_i\beta_j)}{\sum_j^J \exp(x_i\beta_j)}$$

where $P(y_i = j)$ is the probability of belonging to group j, β_j are the estimated coefficients and x_i is a vector of the explanatory (independent) variables. The following terms are integrated to our model as explanatory variables:

COUNTRY	=	Country of origin. Code-Law-Countries: Finland, Germany, Switzerland, Other (Code-Law-Countries), Common-Law-Countries: United Kingdom (UK);
DR	=	Debt Ratio;
IOT	=	Inventories / Turnover;
MSM	=	Measurement method for inventories: FIFO, Weighted Average, FIFO & Weighted Average, Other;
PPEOT	=	PPE / Turnover;
SIC	=	Industry of operations regarding to the SIC classification system (appendix A);
SIZE	=	Size of an entity. Measured by the amount of total balance sheet assets: 1 = 1. quartile (small), 2 = 2. quartile, 3 = 3. quartile, 4 = 4. quartile (large);
YEAR	=	Year of the PPA: Time period of the observation;
ULB	=	Useful life of buildings (in years);
ULO	=	Useful life of other equipment (in years);

In order to control the robustness of our models, we additionally determined MLR models eliminating outlying observations. We identified an observation as an outlier if its corresponding Pearson residual exceeded a quantity of 2 in absolute term (Backhaus, 2008). With this approach, 14 to 16 observations in the case of PPE and 9 to 11 observations in the case of inventories could be determined as outliers, depending on the specific imputation model.

Results

Measuring Goodness of Fit

Table 1 presents the goodness of fit for our models. Since we used multiple imputations, we show our results as a range describing the maximum and minimum of all models. All ratios indicate the feasibility of the models in explaining the frequency of hidden reserves. The likelihood-ratio-chi-square clearly confirms the goodness of all models with a significance of less than 0.000. The pseudo-R^2-ratios also attest an acceptable or rather good fit of the models. It has to be noted that the pseudo-R^2-ratios should not be confused with R^2 of a usual linear regression. A pseudo-R^2 of more than 0.2 already indicates an acceptable goodness of fit, a ratio exceeding 0.4 even indicates a good fit (Tabachnick, &Fidell, 2007).

Table 1. Model Summary - Goodness of Fit

	Number of observations	LR chi^2	Probability > chi^2	Cox&Snell - R^2	Nagelkerke - R^2	McFadden - R^2
PPE	398	176.88 - 180.82	0.000	0.359 - 0.365	0.415 - 0.421	0.222 - 0.227
Inventories	281	164.36 - 179.68	0.000	0.443 - 0.472	0.512 - 0.546	0.292 - 0.320

LR chi^2 = log-likelihood-chi-square; Probability > chi^2 = significance level of the log-likelihood-chi-square;

Cox&Snell, Nagelkerke, McFadden = pseudo-R^2 ratios

Additionally, we have evaluated the classification accuracy of our models. Since our datasets were too small, we could not use a holdout sample for this purpose. Therefore, we compare the classification accuracy of our models with the maximum-chance-criterion (MCC) and the proportional-chance-criterion (PCC). Both ratios can be applied to determine whether or not the hit rates of our models are statistically better than what can be expected by chance. The classification accuracies of our models for PPE reach levels of 63.6% - 65.6%, and therefore clearly exceed both the MCC (43.0%) and PCC (39.0%). Similar results are returned in the case of inventories. Here, we observe classification accuracies of 65.5% - 69.4%, while MCC and PCC amount to 51.6% and 39.7%.

An elimination of outliers does not show a significant alteration in any of the aforementioned criterions. Accordingly, the goodness of fit of our models can be seen as sufficient.

Evaluation of Coefficients

Table 2 provides the range of the log-likelihood-chi-square-value for each variable according to the different imputed MLR models. Most variables reach at least a significance level at less than 5%. Therefore, it would seem that these factors are appropriate to explain differences in the occurrence and frequency of hidden reserves and burdens.

Looking at the log-likelihood-chi-square value it seems that especially the variables SIZE, SIC, COUNTRY and MSM contribute to the goodness of our models. Nevertheless, no significant level in any model can be observed for the variable YEAR and ULB. Moreover, PPEOT indicates weak significance only in a single case.

Table 2. Log-Likelihood

Variable	PPE		Inventories	
	LR chi^2	Probability > chi^2	LR chi^2	Probability > chi^2
Constant	0.000		0.000	
PPEOT	0.931 - 5.473	0.065* - 0.628	-	-
ULO	12.236 - 15.035	0.001*** - 0.002***	-	-
ULB	0.725 - 4.269	0.118 - 0.696	-	-
IOT	-	-	6.0829 - 15.0124	0.001*** - 0.033**
MSM	-	-	32.0282 - 39.0287	0.000***
DR	17.351 - 18.349	0.000***	8.09- 10.0848	0.004*** - 0.012**
SIZE	55.147 - 58.341	0.000***	52.0346 - 57.0583	0.000***
SIC	28.333 - 31.937	0.001*** - 0.005***	33.0904 - 38.0656	0.000***
YEAR	5.142 - 6.314	0.612 -0.742	8.0396 - 10.0530	0.230 - 0.396
COUNTRY	16.715 - 17.768	0.023** - 0.033**	43.0859 - 48.0684	0.000***

LR chi^2 = log-likelihood-chi-square; Probability > chi^2 = significance level of the log-likelihood-chi-square. Based on log-likelihood *, **, *** indicate significance at less than 10%, 5% and 1% level, respectively.

In order to gain better insights to the way in which these variables affect the probability to observe hidden reserves or burdens, it is necessary to analyse the estimated coefficients and odds ratios. The results are shown in Table 3. However, for the purpose of clarity, the table only contains details for the variables that show significance according to Table 2. Therefore, YEAR and ULB are removed in this summary.

Table 3. Estimated Coefficients and Odds Ratios

Panel A: PPE

Variable	y = 1: Hidden Reserves Observed						y = 2: Hidden Burdens Observed					
	Coeff.	Wald	Sign.	Odds ratio	95% conf. interval		Coeff.	Wald	Sign.	Odds ratio	95% conf. interval	
Constant	2.535	9.059	0.003***				1.530	1.995	0.158			
PPEOT	0.000	1.122	0.295	1.000	1.000	1.000	0.000	0.296	0.589	1.000	1.000	1.000
DR	-0.010	9.673	0.002***	0.990	0.984	0.996	-0.016	10.113	0.001***	0.984	0.974	0.994
ULO	0.093	10.033	0.002***	1.098	1.036	1.163	0.049	1.824	0.177	1.050	0.978	1.127
SIZE: < 9.67m EUR	-2.731	34.483	0.000***	0.065	0.026	0.162	-2.940	21.785	0.000***	0.053	0.015	0.182
SIZE: 9.67m - 46.72m EUR	-1.315	10.976	0.001***	0.269	0.123	0.585	-1.949	12.979	0.000***	0.142	0.049	0.411
SIZE: 46.72m - 269.85m EUR	-0.601	2.387	0.122	0.548	0.256	1.175	-0.834	2.982	0.084*	0.434	0.169	1.119
SIZE: > 269.85m EUR	0.000	.					0.000	.				
SIC Division: A,C	-0.900	1.669	0.196	0.407	0.104	1.592	-0.180	0.043	0.837	0.835	0.151	4.618
SIC Division: B	-0.148	0.052	0.820	0.862	0.241	3.081	-0.607	0.448	0.503	0.545	0.092	3.226
SIC Division: D:28	-0.277	0.382	0.536	0.758	0.315	1.825	-0.727	1.053	0.305	0.483	0.121	1.938
SIC Division: E	-1.293	5.884	0.015**	0.274	0.097	0.780	-0.662	0.897	0.344	0.516	0.131	2.030
SIC Division: F&G	-0.116	0.052	0.819	0.891	0.330	2.406	0.836	1.972	0.160	2.308	0.718	7.418
SIC Division: I	-1.665	16.447	0.000***	0.189	0.085	0.423	-1.021	3.460	0.063*	0.360	0.123	1.056
SIC Division: D (Other)	0.000	.					0.000	.				
COUNTRY: Germany	-0.333	0.679	0.410	0.717	0.324	1.583	-0.897	3.340	0.068*	0.408	0.156	1.067
COUNTRY: Finland	-0.804	1.974	0.160	0.447	0.146	1.374	-1.226	2.526	0.112	0.293	0.065	1.331
COUNTRY: Switzerland	-0.835	2.628	0.105	0.434	0.158	1.191	-2.005	6.883	0.009***	0.135	0.030	0.602
COUNTRY: Other (Code Law)	-0.435	1.339	0.247	0.647	0.310	1.352	-1.702	11.401	0.001***	0.182	0.068	0.490
COUNTRY: UK	0.000	.					0.000	.				

(Continued)

Table 3. Continued

Panel B: Inventories

Variable	y = 1: Hidden Reserves Observed						y = 2: Hidden Burdens Observed					
	Coeff.	Wald	Sign.	Odds ratio	95% conf. interval		Coeff.	Wald	Sign.	Odds ratio	95% conf. interval	
Constant	0.905	1.248	0.264				-1.112	1.070	0.301			
IOT	0.014	5.518	0.021**	1.014	1.002	1.026	0.004	0.329	0.568	1.004	0.989	1.020
DR	-0.015	8.567	0.003***	0.985	0.975	0.995	-0.004	0.546	0.460	0.996	0.984	1.007
MSM: Weighted Average	-1.487	9.612	0.002***	0.226	0.088	0.579	1.296	2.888	0.09*	3.654	0.818	16.328
MSM: FIFO&Weighted Average	1.068	1.913	0.168	2.911	0.638	13.272	3.349	10.420	0.002***	28.466	3.690	219.581
MSM: Other	-0.285	0.172	0.679	0.752	0.194	2.908	2.219	6.413	0.012**	9.198	1.649	51.286
MSM: FIFO	0.000	.					0.000	.				
SIZE: < 9.57m EUR	-2.972	25.093	0.000***	0.051	0.016	0.164	-3.161	10.469	0.001***	0.042	0.006	0.288
SIZE: 9.57m - 45.81m EUR	-2.311	18.105	0.000***	0.099	0.034	0.288	-0.381	0.409	0.523	0.683	0.213	2.196
SIZE: 45.81m - 297.66m EUR	-0.912	3.306	0.069*	0.402	0.150	1.074	0.301	0.263	0.608	1.351	0.427	4.272
SIZE: > 297.66m EUR	0.000	.					0.000	.				
SIC Division: A,B,C	-0.938	2.238	0.135	0.392	0.115	1.338	-1.858	4.240	0.039**	0.156	0.027	0.914
SIC Division: D:28	0.793	2.107	0.147	2.211	0.757	6.455	-0.052	0.004	0.950	0.949	0.187	4.825
SIC Division: E	-1.260	4.020	0.045**	0.284	0.083	0.972	-1.837	5.203	0.023**	0.159	0.033	0.772
SIC Division: F&G	-1.617	6.197	0.013**	0.198	0.056	0.709	0.555	0.863	0.353	1.743	0.540	5.626
SIC Division: I	-2.001	4.931	0.026**	0.135	0.023	0.791	-1.381	2.103	0.147	0.251	0.039	1.625
SIC Division: D (Other)	0.000	.					0.000	.				
COUNTRY: Germany	1.236	4.944	0.026**	3.441	1.158	10.230	-1.982	7.511	0.006***	0.138	0.033	0.569
COUNTRY: Finland	-0.768	0.889	0.346	0.464	0.094	2.294	-3.947	8.598	0.003***	0.019	0.001	0.271
COUNTRY: Switzerland	2.701	14.365	0.000***	14.892	3.684	60.202	-0.351	0.147	0.701	0.704	0.117	4.223
COUNTRY: Other (Code Law)	0.869	2.839	0.092*	2.385	0.868	6.557	-0.519	0.854	0.356	0.595	0.198	1.790
COUNTRY: UK	0.000	.					0.000	.				

y = 0 (no hidden reserves or burdens observed) is the reference category. This table presents the combined coefficients (coeff.), wald statistics (wald) and odds ratios (with the corresponding confidence interval) from the imputed MLR models. Based on wald, *, **, *** indicate significance at less than 10%, 5% and 1% level, respectively. PPEOT = PPE/turnover; DR = debt ratio; ULO = useful life of other equipment; SIZE = total balance sheet assets; SIC = industry; COUNTRY = country of origin; IOT = inventories/turnover; MSM = applied measurement method for inventories. Last categories of nominal variables (coeff. = 0) are set as reference category.

Looking at Panel A (PPE), the combined Wald values for the variable PPEOT confirm the assumption regarding the results of Table 2. PPEOT does not seem to contribute to the explanation of the occurrence of hidden reserves and burdens. DR, in contrast, shows high levels of significance. Coefficients and odd ratios indicate that high rates of DR increase the likelihood for the absence of hidden reserves or burdens. Surprising results are given for ULO, since the findings imply that a higher ULO causes a higher probability to observe hidden reserves. Actually, the opposite effect was to be expected. However, at this point the restrictions regarding the level of detail of the data, which have been mentioned in section 3, have to be considered. Since the lack of accuracy for this variable might be a reason for this result, the finding should not be overinterpreted.

The outcome for the variable SIZE, in turn, is again in line with expectations. Smaller entities show hidden reserves and burdens less often than large companies. However, the odds in this context are remarkable anyway. For instance, the odds to show hidden reserves are 15 times (= 0.065/1) lower for the group containing the smallest entities in comparison to the group of the largest companies. A similar relation exists in the case of hidden burdens. There are also interesting findings for the variable COUNTRY. While in the case of hidden burdens our hypothesis *H1b* is at least partially confirmed, our assumption regarding hidden reserves in hypothesis *H1a* must be rejected. None of the code-law-countries has a significant higher likelihood for showing hidden reserves more frequently than the reference category of common-law-countries.

Turning to Panel B (inventories), results for the variables DR, SIC and SIZE are similar to their equivalents in Panel A (PPE). However, findings for the variable COUNTRY are quite different. In contrast to the PPE sample, entities from code-law-countries show hidden reserves more frequently in inventories than the common-law-country companies. Especially Switzerland has high odds in this context.

Also noticeable are the results for IOT and MSM. In the case of IOT, higher ratios indicate a higher likelihood to observe hidden reserves. Against the backdrop of our hypothesis, we were expecting the opposite outcome. An explanation might be that higher ratios of IOT can also imply that entities have more inventories available that can potentially hold hidden reserves. In the case of MSM, especially one finding seems to be remarkable: The odds for showing hidden reserves are four times higher in entities using FIFO compared to entities using the weighted average method. Since FIFO should reflect current market prices more accurately than other methods, this result seems not plausible. Looking at the composition of entities using FIFO, we observe a majority of entities that belong to the manufacturing sector (SIC D). Since entities from this industry often hold more inventories available than companies from other industries, the probability to be affected by hidden reserves might be higher in these cases. Nevertheless, additional research is necessary to clarify this finding. However, our hypothesis regarding MSM seems to be largely confirmed at least in the case of hidden burdens and thus, other methods than FIFO have a higher likelihood for showing hidden burdens.

The elimination of outliers does not change the results substantially. Therefore, our findings indicate the following consequences for our hypotheses (Table 4):

Table 4: Summary Hypotheses

Hypothesis	Variable	Results: PPE	Results: Inventories
H1a	COUNTRY	rejected	partially confirmed
H1b	COUNTRY	partially confirmed	partially confirmed
H2	SIC	confirmed	confirmed
H3	SIZE	confirmed	confirmed
H4	PPEOT	rejected	-
H5	IOT	-	rejected
H6a	DR	confirmed	confirmed
H6b	DR	rejected	rejected
H7a	ULB / ULO	rejected	-
H7b	ULB / ULO	rejected	-
H8	MSM	-	partially confirmed

Conclusions

This paper identifies drivers of hidden reserves in IFRS financial statements and analyses the possible conclusions for the comparability of financial statements. We base our research on a previous study using a sample of 456 Purchase Price Allocations and investigate the observed frequency of hidden reserves for two balance sheet items (PPE and inventories) in this context.

Our results indicate that numerous factors influence the probability to observe hidden reserves under IFRS. Especially the size of an entity, the industry an entity belongs to and the country of origin are substantial drivers. For instance, looking at PPE, large companies show hidden reserves 24 times more often than small entities; also, companies have a 3.5 times smaller chance to hold hidden reserves when they operate in the infrastructure sector (SIC E) instead of the manufacturing industry (SIC D) and finally, there is an almost 7.5 times higher chance for the occurrence of hidden burdens in entities form the UK compared to companies from Switzerland. As far as inventories are concerned, similar findings are valid. Moreover, in this case, measurement of inventories is also a significant driver of hidden reserves, e.g. companies using FIFO show hidden burdens less frequently than entities applying different measurement methods. However, the odds for showing hidden reserves are four times higher in entities using FIFO compared to entities using the weighted average method. Since FIFO should reflect current market prices more accurately than other methods, this result is remarkable.

There are also some surprising outcomes concerning the year of the acquisitions. None of our models show any significance for the variable YEAR of a PPA. This result is interesting, since it might indicate that even events with a huge economic impact on the value of an entity – like the financial crisis – do not influence the frequency of the occurrence of hidden reserves or burdens.

Nevertheless, we also have to point out the limitations of our study. First of all, we have investigated only two balance sheet items. For a more comprehensive view, other positions should be analysed as well. Secondly, we have only investigated the frequency of hidden reserves. It might be interesting to see if the amounts of hidden reserves and burdens differ also significantly between entities from different countries or industries. Thirdly, the variables we used are only proxies. The origin of hidden reserves is actually based on specific measurement options and individual judges a company uses when preparing their financial reports. Therefore, variables like country or size can only indirectly explain the occurrence of hidden reserves. More detailed data is necessary to explain the occurrence of hidden reserves directly. Finally, our study does not disclose the specific consequences hidden reserves or burdens have on financial statement analysis. Therefore, additional research like the study of Rodríguez-Pérez Slof, Solà, Torrent and Vilardell (2011) could build on our findings to show the impact of hidden reserves more precisely.

In Summary, our study clearly implicates that hidden reserves and burdens occur inconsistently between entities from different countries, industries or of a different size. Looking at similar studies in this field, our findings support the assumption that IFRS lead not necessarily to comparable financial statements. Therefore, our results indicate that still more effort has to be made in order to achieve the objective of IFRS in providing useful information to investors and other stakeholders.

References

Backhaus, K. (2008), *Multivariate Analysemethoden* – Eine anwendungsorientierte Einführung [Methods of Multivariate Data Analysis – A Practical Introduction], Berlin: Springer.

Ball, R. (2006), International Financial Reporting Standards (IFRS): pros and cons for investors, *Accounting & Business Research*, Special Issue: International Accounting Policy Forum, pp. 5-27.

Brähler, G., &Schmidt, S. (2014), Hidden Reserves Under IFRS – Empirical Insights, *International Review of Management and Business Research*, 3 (2), pp. 1073-1087.

Callao, S., Ferrer, C., Jarne J. I., & José A. (2009), The impact of IFRS on the European Union: Is it related to the accounting tradition of the countries?, *Journal of Applied Accounting Research*, 10 (1), pp. 33-55.

Cole, V., Branson, J., &Breesch, D. (2011), The Illusion Of Comparable European IFRS Financial Statements. Beliefs Of Auditors, Analysts And Other Users, *Accounting and Management Information Systems*, 10 (2), pp. 106-134.

Cole, V., Branson, J., & Breesch, D. (2013), Determinants influencing the IFRS accounting policy choices of European listed companies. *Working Paper, Available at:* http://ssrn.com/abstract=221749810 .

Fienberg, S. K. (1977), The Analysis of Cross-Classified Data, Cambridge: MIT Press.

Graham, J. W., & Schafer, J. L. (2002), Missing Data: Our View of the State of the Art, *Psychological Methods*, 7 (2), pp. 147-177.

Haller, A., & Wehrfritz, M. (2013), The impact of national GAAP and accounting traditions on IFRS policy selection: Evidence from Germany and the UK, *Journal of International Accounting, Auditing & Taxation*, 22 (1), pp. 39-56.

Hellman, N. (2008), Accounting Conservatism under IFRS, *Accounting in Europe,* 5 (2), pp. 71-100.

Hosmer, D. W., & Lemeshow, S. (2000), Applied Logistic Regression, 2nd ed. New York: Wiley.

Ibrahim, J.G., Chen, M.H., Lipsitz, S.R., & Herring, A.H. (2005), Missing-Data Methods for Generalised Linear Models: A Comparative Review, *Journal of the American Statistical Association*, 469, pp. 332-346.

Jaafar, A., & McLeay, S. (2007), Country Effects and Sector Effects on the Harmonization of Accounting Policy Choice, *ABACUS*, 43 (2), pp. 156-189.

Kvaal, E., & Nobes, C. (2010), International differences in IFRS policy: A research note, *Accounting and Business Research*, 40 (2), pp. 173-187.

Kvaal, E., & Nobes, C. (2012), IFRS Policy Changes and the Continuation of National Patterns of IFRS Practice, *European Accounting Review*, 2 (2), pp. 343-371.

Lara, J. M. G., & Mora, A. (2004), Balance Sheet versus Earnings Conservatism in Europe, *European Accounting Review*, 13 (2), pp. 261-292.

Liao, Q., Sellhorn, T., & Skaife, H. (2012), The Cross-Country Comparability of IFRS Earnings and Book Values: Evidence from France and Germany, *Journal of International Accounting Research*, 11 (1), pp. 155-184.

Martin, R. D., Rich, J. S., & Wilks, J. T. (2006), Auditing Fair Value Measurements: A Synthesis Of Relevant Research, *Accounting Horizons*, 20 (3), pp. 287-303.

Nobes, C. (2011), IFRS Practices and the Persistence of Accounting System Classification, *ABACUS*, 47 (3), pp. 267-283.

Nobes, C. (2013), The continued survival of international differences under IFRS, *Accounting and Business Research*, 43 (2), pp. 83-111.

Nobes, C., & Perramon, J. (2013), Firm Size and National Profiles of IFRS Policy Choice, *Australian Accounting Review*, 23 (3), pp. 208-215.

Penman, S. H. (2007), Financial reporting quality: is fair value a plus or a minus?, *Accounting and Business Research*, Special Issue: International Accounting Policy Forum, pp. 33-44.

Penman, S. H., & Zhang, X. (2002), Accounting conservatism and the quality of earnings, and stock returns, *The Accounting Review,* 77 (2), pp. 237-264.

Quagli, A., & Avallone, F. (2010), Fair Value or Cost Model? Drivers of Choice for IAS 40 in the Real Estate Industry, *European Accounting Review, 19 (3), pp. 461-493.*

Rodríguez-Pérez, G., Slof J., Solà, M., Torrent, M.-R., & Vilardell, I. (2011), Assessing the Impact of Fair-Value Accounting on Financial Statement Analysis: A Data Envelopment Analysis Approach, *ABACUS,* 47 (1), pp. 61-84.

Salter, S. B., Kang, T., Gotti, G., & Doupnik, T. S. (2013), The Role of Social Values, Accounting Values and Institutions in Determining Accounting Conservatism, *Management International Review*, 53, pp. 607-632.

Tabachnick, B. G., & Fidell, L. S. (2007): *Using multivariate statistics*. 5th ed. Boston: Pearson/Allyn & Bacon.

Watts, R. L. (1992), Accounting Choice Theory and Market Based Research, *British Accounting Review*, 24, pp. 235-267.

Watts, R. L. (2006), What has the invisible hand achieved*?, Accounting & Business Research*, 36 (Special Issue), pp. 51-61.

Watts, R. L., & Zimmerman J. (1990), Positive Accounting Theory: A Ten Year Perspective, *Accounting Review*, 65 (1), pp. 131-156.

Whittington, G. (2006), Fair Value and the IASB/FASB Conceptual Framework Project: An Alternative View, *ABACUS*, 44 (2), pp. 139-168.