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Abstract

We contribute to the value relevance literature by investigating critical methodological deficiencies emerged in past and current empirical research. Using Monte Carlo simulations calibrated on the basis of the statistical properties of market and accounting data for a large sample of European listed companies, we are the first to document and quantify the effects of neglecting the lag of stock price as an explanatory variable in the conventional approach for estimating price level regressions. We demonstrate that for European listed companies this is an important source of omitted variable bias and the extent of such bias increases as the autocorrelation coefficient for stock price and the explanatory variables increases. We show that using alternative specifications which deflate the accounting variables by the lag of stock price, commonly employed in the accounting literature, can lead to high over-rejection rates. Our findings are relevant for the interpretation of most of the empirical studies on the impact of IFRS on value relevance in Europe.

Keywords: *Value relevance; Linear Information Model; IFRS; Monte Carlo simulations; Price Regression Mode; Panel data models*

"The last rule was to make enumerations so complete, and reviews so comprehensive, that I should be certain of omitting nothing."

René Descartes, Discourse on Method (1637)

1. Introduction

In this study we critically address key econometric deficiencies that arise in value relevance studies because of a lack of understanding of the process generating the variables in value relevance models.

Value relevance studies aim to assess the extent to which accounting data reflect information that is "relevant" for firm value as represented by the stock price. Over the last decades, the literature has honed in on a broad range of types of accounting information. Examples include accounting for investment securities, goodwill and fair value (Holthausen and Watts, 2001).

There are two main approaches to measure value relevance (Hellström, 2006): studies based on the 'signalling perspective' focus on changes in market-based variables following announcements related to the release of accounting information; on the other hand, studies focussing on the 'measurement perspective' are based on regression models where the regressand is a stock market variable (stock price or return) while the regressors are accounting variables such as book value of equity, earnings, and changes in earnings. In this study, we focus on the latter perspective.

Following the seminal works by Ohlson (1995) and Feltham and Ohlson (1995), most empirical studies rely on modified versions of the Linear Information Model (LIM), which models firm value as a function of book value of equity and expected future abnormal earnings (Collins et al., 1997; Aboody et al., 2002). The LIM is based on the assumption of clean surplus accounting, implying that the current book value of equity is equal to the book value of equity from the previous year plus current earnings, net of dividends and share repurchases/offerings. The LIM has been hailed as "among the most important developments in capital markets research" Bernard (1995, p. 733): its main innovation is the departure from classical valuation models based on dividends[1] – the LIM provides a direct link between accounting figures reported in financial statements and firm value.

Researchers employ the R-squared of regressions developed from the LIM as a measure of value relevance: the higher the R-squared, the higher the value relevance. However, this procedure has several limitations: in particular, scale effects can give rise to inflated R-squared values in regressions

[1] For a comparison between valuation models based on dividends and Ohlson-Feltham models, see Dechow et al. (1999).

where the stock price is the dependent variable (Easton, 1998; Brown et al., 1999).[2] On the other hand, using stock returns as regressand can lead to R-squared values that are too low (Lev, 1989).

A common approach for dealing with scale effects in panel data is to deflate all variables by a common factor (for example, the lag of stock price, as in Lang et al., 2006). This procedure is supposed to allow for heteroskedasticity, which can result in wrong R-squared values and biased t-statistics for the individual coefficients (Barth and Clinch, 2009). However, the literature is mixed with regard to what variable should be chosen as deflator (Dedman et al., 2009).

Importantly, as pointed out by Bhargava (2010), combining variables into ratios can result in wrong inferences, and this problem is exacerbated in panel data because the stochastic properties of the two variables comprising the ratio may evolve differently over time. Moreover, this method does not eliminate firm-level time-invariant components of the error term which may, in certain cases, lead to inconsistency of the coefficient estimates (Devalle et al., 2010). [3]

Table 1 reports value relevance studies which employ price-level regressions, also known as the Price Regression Model (PRM).[4] Among these papers, only Devalle et al. (2010) and Agostino et al. (2011) make use of panel data models.

[Insert Table 1 Here]

In this paper, we focus on the impact of unsuitable econometric specifications on the coefficient estimates of price level regressions and related specifications that use the lag of stock price as a deflator. The validity of the coefficient estimates of price level regressions is a key topic in the value relevance literature. For example, Kothari and Zimmerman (1995) assess the extent to which price level regressions fit the theoretical prediction of a random walk in earnings. Barth and Kallapur (1996) show that deflating the variables by a scale proxy does not usually solve the problem of coefficient bias due to an omitted scale proxy (and in certain cases may *worsen* the problem), while including a scale proxy as an explanatory variable mitigates coefficient bias. Relatedly, Aboody et al. (2002) investigate the impact of market inefficiency on the coefficient estimates of price level

[2] This limitation is particularly troublesome for researchers wishing to compare the explanatory power of the model in two or more sub-samples. This may occur, for instance, when investigating value relevance across countries, or in studies about the effects of a new regulation on value relevance, which requires estimation of the R-squared in the pre-reform and post-reform period.

[3] This problem can be addressed by including firm fixed-effects in the regressions. Much of the value relevance literature does not consider firm fixed-effects, although some studies include country and industry fixed-effects (for instance, Barth et al., 2014).

[4] In this list, we consider papers published over the period 2000-2014 in the following major accounting journals: Australian Accounting Review; European Accounting Review; Journal of Accounting and Economics; Journal of Accounting Research; Journal of Accounting, Auditing and Finance; Journal of Business Finance & Accounting; Journal of International Accounting, Auditing and Taxation; Journal of International Financial Management & Accounting; Review of Accounting Studies; Review of Quantitative Finance and Accounting.

regressions. Importantly, none of these papers focus on coefficient bias resulting from autocorrelation of the variables in the PRM. We demonstrate that for studies on European listed firms this source of bias is very likely to be a serious concern, and we show that it can also be easily allowed for by using dynamic panel data models. While these models are often employed in the corporate finance literature, they have, to the best of our knowledge, never been employed in the value relevance literature.

Clearly, questioning the validity of the coefficient estimates of price level regressions is of paramount importance to make sense of the findings of the empirical literature, and in certain cases bears important implications for policy. This is the case for recent empirical papers that attempt to evaluate the impact of International Financial Reporting Standards (IFRS) on value relevance focusing on the coefficient estimates of the book value per share and earnings per share (Gjerde et al., 2008; Devalle et al., 2010). Therefore, an investigation of the validity of the coefficient estimates is essential to evaluate the validity of the policy recommendations of these papers (Holthausen and Watts, 2001). Our study is motivated by recent concerns in both the academia and professional bodies about the lack of consistency in the methodology employed in the value relevance literature, especially for studies on the implementation of IFRS, which in turn undermines the comparability of the findings for different countries (Veith and Werner, 2014; ICAEW, 2014).

Our analysis of the empirical statistical properties of stock prices, book values of equity per share, and earnings per share for a large sample of European companies documents that these variables are very likely to follow an autoregressive process. Because of such autocorrelation, any correlation between the current value of stock price and the current value of one of the explanatory variables spills over to the lag of stock price. Thus, omitting the lag of the stock price from price level regressions will lead to omitted variable bias (OVB) if there is a strong autocorrelation in stock price and correlation between stock price and any explanatory variable. While this problem may not affect the explanatory power of the model and the rejection rate for the null hypotheses that the coefficients on book value of equity per share (BVPS) and earnings per share (EPS) are different from zero, it clearly undermines the ability of the PRM to capture the true relationship between accounting figures and the market value of the firm. The standard PRM is not the only model affected by an autoregressive stock price. Even modifications of the PRM that use the lag of stock price as a common deflator may be misspecified and lead to wrong inferences.

We offer four important contributions to the literature. First, we show that the empirical autocorrelation function for both the dependent and the independent variables of the PRM exhibits a strongly significant and positive first-order autocorrelation coefficient and there is also a significant correlation between the lag of stock price and the explanatory variables.[5] The combination of these two features can lead to OVB if the lag of stock price is not included in the regressions.

Second, we show that estimating the PRM using Ordinary Least Squares (OLS) with clustered standard errors and omitting the lag of stock price from the regression (the most common approach in empirical accounting studies) results in an economically significant bias of the coefficients of the explanatory variables which are correlated with the current stock price. The bias persists when firm-fixed effects are added to the specification. Adding the lag of stock price to the specifications helps reduce the bias in the coefficients of the explanatory variables correlated with the lag of price. However, in this case, one must use a dynamic panel data model to allow for the "dynamic panel bias" (Nickell, 1981).

Third, we show that modifications of the standard PRM based on the lag of stock price as a common deflator may result in invalid t-statistics if the process generating the variables in the model is autoregressive. In particular, these models tend to reject of the null hypothesis of no correlation between market data and accounting data too often when the null hypothesis is true.

Finally, while we are aware of the large bulk of literature on the consequences of scale effects on rejection rates and coefficient bias calibrated using data from Compustat for US firms, this is to the best of our knowledge the first study of this kind on a large sample of European listed firms.

The structure of the rest of the paper is as follows. Section 2 explains the theory and estimation of value relevance models based on the LIM. Section 3 examines the autocorrelation properties of the variables of the PRM for a sample of European listed firms. Section 4 reports the results of Monte Carlo simulations. Section 5 concludes the paper.

2. Value relevance models: theory and application

2.1 The Ohlson (1995) and Feltham and Ohlson (1995) approach

The starting point of value relevance studies based on the "measurement" approach is the LIM (Ohlson, 1995; Feltham and Ohlson, 1995), which relates the market value of equity to the book value of equity and the present value of abnormal earnings:

$$V_t = B_t + \sum_{\tau=1}^{\infty} R^{-\tau} E_t\left[x_{t+\tau}^a\right] \tag{1}$$

[5] In this paper, we employ the terms "autocorrelation" and "serial correlation" interchangeably.

where V is the market value of equity, B is the book value of equity, t is the current period while τ denotes the number of periods from period t (so that $t + \tau$ is a future period and $t - \tau$ is a past period), R is $(1 + r)$, where r is the one-period interest rate, $E[.]$ is the expectations operator, and $x_t^a = x_t - rB_{t-1}$ denotes abnormal earnings (actual earnings for period t, x_t, minus "normal" earnings, rB_{t-1}). The only assumption required for (1) to hold is the clean surplus relation:

$$B_t = B_{t-1} + x_t - D_t - S_t \tag{2}$$

where D denotes dividends and S share repurchases (the latter can be negative in case of share offerings). However, the LIM also involves a prediction on how future abnormal earnings are related to current abnormal earnings:

$$\begin{aligned} x_{t+1}^a &= \omega x_t^a + v_{t-m} + \varepsilon_{1,t+1} \\ v_{t+1} &= \gamma v_t + \varepsilon_{2,t+1} \end{aligned} \tag{3}$$

where v represents information incorporated in the market value of equity other than the information captured by book value of equity and earnings, and $m \geq 0$, $0 \leq \omega \leq 1$ and $0 \leq \gamma \leq 1$ are persistence parameters. Clearly, the autoregressive nature of both B and x^a as described by (2) and (3) has an impact on V.

For convenience, consider the case for which $E_t\left[x_{t+\tau}^a\right] = 0$ for $\tau > 1$, and assume $E[\varepsilon_{1,t+1}] = E[\varepsilon_{2,t+1}] = 0$, with $m = 0$ (Ohlson, 1995). Combining (1)-(3), we obtain:

$$\begin{aligned} V_t &= B_t + R^{-1}\left\{\omega\left(x_t - rB_{t-1}\right) + \gamma\left[\omega\left(x_{t-1} - rB_{t-2}\right) - \omega^2\left(x_{t-2} - rB_{t-3}\right)\right]\right\} \\ V_{t-1} &= B_{t-1} + R^{-1}\left\{\omega\left(x_{t-1} - rB_{t-2}\right) + \gamma\left[\omega\left(x_{t-2} - rB_{t-3}\right) - \omega^2\left(x_{t-3} - rB_{t-4}\right)\right]\right\} \end{aligned} \tag{4}$$

Therefore, V depends on the current and past values of B and x, which are both autoregressive processes, leading to correlation between V_t and V_{t-1}, as long as $0 < \omega \leq 1$ and $0 < \gamma \leq 1$. In particular, both V_t and V_{t-1} depend, in this case, on x_{t-1}, x_{t-2}, B_{t-1}, B_{t-2}, B_{t-3}. If we assume absence of persistence in v, (4) boils down to:

$$\begin{aligned} V_t &= B_t + R^{-1}\left[\omega\left(x_t - rB_{t-1}\right)\right] \\ V_{t-1} &= B_{t-1} + R^{-1}\left[\omega\left(x_{t-1} - rB_{t-2}\right)\right] \end{aligned} \tag{5}$$

In this case, as long as $0 < \omega \leq 1$, both V_t and V_{t-1} depend on B_{t-1}. On the other hand, relaxing the assumption $E_t\left[x_{t+\tau}^a\right] = 0$ for $\tau > 1$ leads to an even stronger persistence in V, all other things being equal.

In Figure 1 we show how the autocorrelation coefficients for the book value of equity and the market value of equity changes with ω, if V_t follows an Ohlson-type process based on equations (1)-(3). The simulations are based on fictitious data on 500 firms and 40 years, considering $0.01 \leq \omega \leq 1$.[6] In particular, we assume a relatively moderate growth in the economy, with an initial interest rate of 3% which follows a random walk. In Figure 2 we show the same graph assuming an initial rate of 12%. The graphs clearly show an autocorrelation coefficient very close to one, regardless of the value for ω. Therefore, if the market value of equity and book value of equity of firms follow an Ohlson-type of process, we can expect a very strong autocorrelation component in the stock price and book value of equity per share, and potentially even non-stationarity. For high values of ω even the earnings per share will have an autocorrelation coefficient close to one.

[Insert Figures 1 and 2 Here]

2.2 Estimating the coefficients of the PRM

Typically, the PRM involves estimating a regression of stock price on book value and earnings (net income) per share (Barth et al., 2008).[7] We consider two possible models for estimating the PRM:

$$P_{it} = a + bBVPS_{it} + cEPS_{it} + e_{it} \quad (6)$$

$$P_{it} = a + \rho P_{it-1} + bBVPS_{it} + cEPS_{it} + e_{it} \quad (7)$$

where $i = 1, 2, ..., N$ represent firms, $t = 1, 2, \ldots, T$ represent years, and $|\rho| < 1$.

The literature has so far considered only model (6) and related modifications. We focus on this model because it is less likely to be prone to scale effects than models based on the market value of equity, book value of equity, and earnings. One can estimate model (6) using a pooled OLS regression, with Huber/White standard errors clustered on the firm level to allow for intra-group correlation in the error term.[8] However, model (6) can also be estimated using a Random Effect (RE) model, or a Within-Group (WG) regression, similar to Devalle et al. (2010). These models assume that the error term e_{it} comprises a time-invariant firm-specific component (the firm fixed-effect), $\eta_i \sim N(\eta, \sigma_\eta^2)$, and an idiosyncratic component, $\varphi_{it} \sim N(0, \sigma_\varphi^2)$. The RE model assumes that η_i are distributed randomly across firms, and is consistent as long as $\text{Cov}(\eta_i, \boldsymbol{x}_{it}) = 0$ where $\boldsymbol{x}_{it}$ represent any

[6] More details on the values employed to calibrate the simulations are given in the appendix.
[7] Some studies also use market value of equity, book value of equity, and earnings, rather than the per share figures, and in certain cases the variables are adjusted for scale effects through a common deflator. For a good explanation of the consequences of using different specifications and deflators, see Barth and Clinch (2009).
[8] This can be implemented in STATA using the command "reg *depvar indepvar*, cluster(*id*) robust".

of the explanatory variables in (6). The latter treats η_i as a nuisance parameter and eliminates it by subtracting the firm-level mean of each variable for all observations. In so doing, the WG model eliminates any firm-specific time-invariant omitted variable which may be correlated with any of the explanatory variables. For this reason, the WG model can be applied even in cases for which the condition Cov(η_i, $\boldsymbol{x_{it}}$) = 0 is violated.[9]

We also estimate (7) using WG to explore the extent to which neglecting the autoregressive nature of P can lead to OVB. Therefore, in the case of (6) and (7), the estimated regressions are, respectively:

$$P_{it} - \overline{P}_i = b\left(BVPS_{it} - \overline{BVPS_i}\right) + c\left(EPS_{it} - \overline{EPS_i}\right) + \eta_i - \eta_i + \varphi_{it} - \overline{\varphi}_i \tag{8}$$

$$\begin{aligned} P_{it} - \overline{P}_i = {} & \rho\left(P_{it-1} - \overline{P}_i\right) + b\left(BVPS_{it} - \overline{BVPS_i}\right) + c\left(EPS_{it} - \overline{EPS_i}\right) \\ & + \eta_i - \eta_i + \varphi_{it} - \overline{\varphi}_i \end{aligned} \tag{9}$$

where $\overline{P}_i$, $\overline{BVPS_i}$, $\overline{EPS_i}$ and $\overline{\varphi}_i$ are the firm-level averages for P, $BVPS$, EPS, and φ. Clearly, the demeaning process of WG estimator eliminates η_i and allows for the influence of any omitted time-invariant variable.[10] Therefore, estimating (6) according to (8) should lead to unbiased and consistent estimates as long as the OVB is due solely to violation of the condition Cov(η_i, $\boldsymbol{x_{it}}$) = 0.[11]

Estimating (7) according to (9) results in Cov(φ^*_{it} , $P^*_{it\text{-}1}$) $\neq$ 0, where $\varphi^*_{it} = \varphi_{it} - \overline{\varphi}_i$ and $P^*_{it-1} = P_{it-1} - \overline{P}_i$ (Nickell, 1981).[12] This OVB problem generates from the negative correlation between $P_{it-1} - \frac{1}{T-1}\left(P_{i1} + \ldots + P_{it} + \ldots P_{iT-1}\right)$ and $\varphi_{it} - \frac{1}{T-1}\left(\varphi_{i2} + \ldots + \varphi_{it} + \ldots \varphi_{iT}\right)$ which, as described in Bond (2002), does not vanish as the sample increases, leading to a downward bias (and inconsistency) for the WG estimate of ρ.[13] This problem is commonly known as "dynamic panel bias" (Nickell, 1981).

To address this OVB problem, one can employ a method developed by Arellano and Bond (1991) based on Generalised Method of Moments (GMM). This method eliminates η_i by first-differencing

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[9] An example of such omitted variables may be firm size, leading to well-known scale effects (Barth and Grinch, 2009).

[10] A less parsimonious alternative would be to employ a Least Squares Dummy Variables (LSDV) approach, which allows for firm fixed-effects by a series of firm dummies.

[11] In conjunction with the WG estimator (implemented in the software package STATA by the command "xtreg depvar indepvars, fe"), the option "robust" produces a consistent variance matrix estimator of the errors by allowing for non-identically distributed errors across firms (because of, for example, size-induced scale effects) or firm-level serial correlation in the errors of fixed order (Stock and Watson, 2008).

[12] The discussion in this section borrows heavily from Roodman (2006) and Bond (2002).

[13] Conversely, the estimate of ρ using OLS will be *upward* biased.

the data, and allows for Cov(φ^*_{it} , P^*_{it-1}) ≠ 0 via an Instrumental Variables (IV) approach: the lags of dependent variable (in levels) are used as instruments for the first-differenced lag of the dependent variable. First-differencing has an important advantage as compared to the within-group transformation: the transformation affects only the first lag of the error term instead of all of them. For this reason, as long as the disturbances, φ_{it} , are uncorrelated,[14] one can obtain consistent estimates of ρ by using instruments that are correlated with $\Delta P_{it-1} = P_{it-1} - P_{it-2}$ and uncorrelated with $\Delta\varphi_{it}$. For instance, P_{it-2} can be employed as instruments for ΔP_{it-1}, because it satisfies both an exclusion condition, $\mathrm{E}[P_{it-2}\Delta\varepsilon_{it}] = 0$, and a relevance condition, $\mathrm{E}[P_{it-2}\Delta P_{it-1}] \neq 0$. To increase the efficiency of the estimator, Arellano and Bond (1991) suggest that even further lags (P_{it-3},P_{it-4}, and so on, until P_{iT-2}) be used in the estimation.

The Arellano and Bond (1991) estimator is commonly known as Difference GMM (GMM-DIF), because it is based on first-differenced regressions. Arellano and Bover (1995) and Blundell and Bond (1998) improve the GMM-DIF estimator by including a system of first-differenced and levels equations, where lags of levels (in the former) and lags of the first-differences (in the latter) are employed as instruments. When ρ is large, as it is likely to be the case when estimating (7) (see Section 3), the performance of the GMM-DIF estimator tends to be poor, because the lagged levels of P_{it-1} are weak instruments for ΔP_{it-1} (Blundell and Bond, 1998; Roodman, 2006).[15] In the appendix we report further details regarding the instruments employed by GMM-DIF and GMM-SYS.

2.3 Alternative specifications

Some authors have employed alternative specifications to the classical PRM. In this section, we examine the impact of autocorrelation in stock price, earnings, and book values on estimation of these models.

A common approach is to focus on stock returns, instead of stock prices. This model is known as Return Regression Model (RRM), and is generally based on a regression of stock returns on earnings per share and changes in earnings per share:

$$RET_{it} = a + bEPS_{it} / P_{it-1} + c\Delta EPS_{it} / P_{it-1} + e_{it} \tag{10}$$

[14] Note that this assumption implies absence of AR(2)-type correlation for the disturbances in the regression in first-differences, $\Delta\varphi_{it}$. However, AR(1) correlation in $\Delta\varphi_{it}$ does not invalidate the assumptions of the model.

[15] The System GMM (GMM-SYS) can be implemented in STATA with the user-written command "xtabond2", or with the built-in command "xtdpdsys". We prefer the former because its flexibility facilitates the comparison of the performance of the WG estimator with that of the GMM-SYS estimator in conditions of autoregressive variables. In particular, we will employ the two-step version of this estimator, with the standard errors corrected using Windmeijer (2005) finite-sample adjustment, to estimate model (7). For more information on how to implement the command "xtabond2" in STATA, see Roodman (2006).

where $RET_{it} = \dfrac{P_{it} + DPS_{it} - P_{it-1}}{P_{it-1}}$ and $\Delta EPS_{it} = EPS_{it} - EPS_{it-1}$ (Barth and Clinch, 2009).

An alternative specification to the original PRM involves deflating every variable by the lag of stock price. This class of adjustment should allow for scale effects:[16]

$$P_{it} / P_{it-1} = a + bBVPS_{it} / P_{it-1} + cEPS_{it} / P_{it-1} + e_{it} \tag{11}$$

3. Statistical properties of actual market and accounting data

3.1 Sample construction

To empirically examine the statistical properties of actual financial data used in the PRM, we collect data for a large sample of European listed companies from *Amadeus* for 17 European countries: *Austria*, *Belgium*, *Denmark*, *Finland*, *France*, *Germany*, *Greece*, *Ireland*, *Italy*, *Luxembourg*, *Netherlands*, *Norway*, *Portugal*, *Spain*, *Sweden*, *Switzerland,* and the *United Kingdom*. We choose these countries because most of the recent value relevance studies have focused on Western Europe, especially to assess the impact of the mandatory adoption of IFRS on value relevance. In particular, our sample comprises the same countries used in a recent study by Barth et al. (2014), plus *Austria* and *Luxembourg*. The cross-country nature of our sample enables us test the robustness of our analysis across different institutional, regulatory and cultural settings (Christensen et al., 2013; Veith and Werner, 2014). Price data are collected from *Datastream* and accounting data from *Amadeus*. Data availability for our main variables of interest (*P*, *BVPS*, and *EPS*, and the respective first lags) during the sample period 2003-2013 results in 2,888 companies selected.

3.2 Estimating the PRM

We begin our analysis by investigating the first-order autocorrelation coefficient for the main variables of interest. Table 2 reports the results of this simple analysis for the whole sample and for 17 sub-samples, one for each country. Consistent with previous literature, we use as dependent variable *P*, the stock price as at six months after fiscal year-end (Lang et al., 2003; Lang et al., 2006; Barth et al., 2008). To make our analysis more comparable to that by Barth et al. (2008), we also regress *P* on country and industry fixed-effects,[17] and consider the residuals of this regression, *P**, in our analysis. The results show a strong degree of first-order autocorrelation: for the whole sample and all of the country sub-samples there is a significant first-order autocorrelation coefficient. Regressing *P* on country and industry fixed-effects does not reduce the magnitude of first-order autocorrelation.

[16] Note that both (10) and (11) reduce the possibility that a dynamic model is necessary, and eliminate the possibility of non-stationarity if P_{it} is an autoregressive process integrated of order one, or I(1).
[17] To obtain the industry fixed-effects, we consider the primary 2-digit SIC code.

Moreover, in many cases the coefficient is close to one, suggesting that some of the variables may be close to non-stationarity. For this reason, the GMM-SYS model appears more appropriate that the WG and even the GMM-DIF model.

[Insert Table 2 Here]

In Table 3 we investigate whether there is correlation between the lag of *P* and *P** and the explanatory variables of the PRM: *BVPS* and *EPS*. The results reported show that, apart from very few instances, there is a positive and significant correlation between the lag of stock price and the explanatory variables in the PRM. In many cases, the correlation coefficient is larger than 0.6. Therefore, omitting the lag of the stock price from the analysis is likely to induce significant OVB in the analysis.

[Insert Table 3 Here]

In Table 4 we report the results for three different specifications for the PRM:

- Pooled OLS regression with heteroskedasticity-robust standard errors, clustered on the firm level based on model (6);
- WG regression with heteroskedasticity-robust standard errors, clustered on the firm level based on model (6);
- WG regression with heteroskedasticity-robust standard errors, clustered on the firm level based on model (7);

The results clearly suggest that the type of specification chosen has a strong impact on inferences. The most common specification in empirical accounting studies, the first specification, suggests that there is no correlation between *P* or *P** and the explanatory variables *BVPS* and *EPS*. On the other hand, for the WG models the coefficient on *BVPS* is positive and significant. However, including the lag of stock price as explanatory variable results in a considerable reduction of the magnitude of the coefficient on *BVPS* (around 0.7 and 0.8). The coefficient on the lag of stock price is positive and significant, and its magnitude (around 0.8-0.9) is in line with the results reported in Table 3. These results clearly point towards what we expected: there is a serious OVB problem in PRM that omit the lag of stock price on the right-hand side of the regression.

[Insert Table 4 Here]

An additional issue is whether firm fixed-effects should be included in the regressions because of the presence of firm-specific time-invariant components in the error term correlated with one or more of the explanatory variables, that is, Cov(η_i, $\boldsymbol{x}_{it}$) $\neq 0$. If this is the case, one should employ a WG regression to avoid inconsistency of the coefficient estimates (or equivalently, an LSDV model). Conversely, if Cov(η_i, $\boldsymbol{x_{it}}$) = 0, a RE regression would result in higher efficiency, and should thus be preferred. Typically, researchers employ a Hausman test to decide between a WG or a RE regression, where the null hypothesis is Cov(η_i, $\boldsymbol{x_{it}}$) = 0, and rejection of this hypothesis leads to inconsistency of the RE estimates. In Table 5 we report the P-value for Hausman tests using model (6). In all instances except for Luxembourg, for which the number of observations is negligible, the Hausman test suggests that the RE estimates will be inconsistent because of the presence of firm fixed-effects.

[Insert Table 5 Here]

In Section 4, we resort to a simulation exercise to better pinpoint the effects of omitting the lag of the stock price in the PRM. Moreover, we examine the dynamic panel bias when employed WG regressions instead of the GMM-SYS method.

4. Monte Carlo simulations

4.1 Simulating PRM variables

In this section we use simulated data to explore the impact of neglecting the autoregressive nature of *P*, *BVPS* and *EPS*. Unlike Barth and Clinch (2009), who base their simulations on a modified version of the LIM, we calibrate our simulations on the basis of the statistical properties of the sample reported in Section 3.

First, we generate a dataset with 2,000 fictitious firms and ten fictitious periods: i = 1, 2, …, 2000 and t = 1, 2, …, 10. Therefore, our dataset contains 20,000 observations. However, in the regressions we lose one period because of the need to include the first lag of *P*, which results in 18,000 observations for each regression. Then, we simulate the data for *P*, *BVPS*, and *EPS*. The Monte Carlo simulations are based on the following six Data Generating Processes (DGP):

Simulations a):[18]

i)

$P_{it} = 0.8P_{it-1} + u_{1,\text{it}}$ $\quad BVPS_{it} = 0.8BVPS_{it-1} + u_{2,\text{it}}$ $\quad EPS_{it} = 0.8EPS_{it-1} + u_{3,\text{it}}$

[18] Clearly, in the long term, earnings are positively correlated with book value of equity. In these simulations, however, we are only interested in the econometric effect of neglecting the autoregressive nature of these variables, and in particular of P_{it}, rather than the theoretical model underlying the DGP of all three variables. Independence between $BVPS_{it}$ and EPS_{it} has the additional benefit of avoiding multicollinearity, and therefore allows a more straightforward interpretation of the results. Moreover, as long as the clean surplus relation maintains, any change in earnings can be offset by a change in dividends and share repurchases (or offerings). For this reason, an increase (decrease) in EPS_{it} needs not lead to an increase (decrease) in $BVPS_{it}$, at least in the short term.

ii)

$P_{it} = 0.9P_{it-1} + u_{4,\text{it}}$ $BVPS_{it} = 0.9BVPS_{it-1} + u_{5,\text{it}}$ $EPS_{it} = 0.9EPS_{it-1} + u_{6,\text{it}}$

Simulations b):

i)

$P_{it} = 0.8P_{it-1} + 0.4BVPS_{it} + u_{7,\text{it}}$ $BVPS_{it} = 0.8BVPS_{it-1} + u_{8,\text{it}}$ $EPS_{it} = 0.8EPS_{it-1} + u_{9,\text{it}}$

ii)

$P_{it} = 0.9P_{it-1} + 0.4BVPS_{it} + u_{10,\text{it}}$ $BVPS_{it} = 0.9BVPS_{it-1} + u_{11,\text{it}}$ $EPS_{it} = 0.9EPS_{it-1} + u_{12,\text{it}}$

Simulations c):

i)

$P_{it} = 0.8P_{it-1} + 0.4BVPS_{it} + 0.2EPS_{it} + u_{13,\text{it}}$

$BVPS_{it} = 0.8BVPS_{it-1} + u_{14,\text{it}}$ $EPS_{it} = 0.8EPS_{it-1} + u_{15,\text{it}}$

ii)

$P_{it} = 0.9P_{it-1} + 0.4BVPS_{it} + 0.2EPS_{it} + u_{16,\text{it}}$

$BVPS_{it} = 0.9BVPS_{it-1} + u_{17,\text{it}}$ $EPS_{it} = 0.9EPS_{it-1} + u_{18,\text{it}}$

Where the error terms, u, are standard normal variables with mean zero and variance one. As can be seen from the formulas above, for a) P is unrelated to either $BVPS$ or EPS, for b) P is correlated with $BVPS$ (with coefficient 0.4), and for c) P is correlated with both $BVPS$ (with coefficient 0.3) and EPS (with coefficient 0.2). For each simulation, we estimate (6) using both a pooled OLS and a WG regression, and we estimate (7) using both a WG and a GMM-SYS regression. Therefore, as it is common in the literature, we *do not* estimate the equations for $BVPS$ and EPS, but only the one for P.[19]

As a preliminary analysis, we examine the average correlation coefficient between the lag of P (*Plag*) and the explanatory variables for b) and c). For b.i), the average correlation coefficient between *Plag* and *BVPS* is 0.457, with a minimum of 0.427 and a maximum of 0.487. For b.ii) these values are: 0.564, 0.538, and 0.591. For c.i), the average correlation between *Plag* and *BVPS* is 0.418 (minimum 0.384 and maximum 0.448), and the average correlation between *Plag* and *BVPS* is 0.209

[19] For an application of simultaneous equations models to the price-earnings relation, see Beaver et al. (1997).

(0.156, and 0.259). For c.ii) these values are: 0.512 (0.475, and 0.541); and 0.256 (0.198, and 0.307). Therefore, the average correlation rate between *Plag* and the explanatory variables is substantial, and is likely to result in OVB. Also, note that these correlations are on average lower than what reported in section 3 for a sample of European firms. Therefore, in actual datasets, one could expect an even stronger OVB than the one we will report shortly below.

4.2 Results for the Monte Carlo simulations: PRM

Table 6 reports the results for the Monte Carlo simulations. Panel A reports the results for model (6), using an OLS regression and a WG regression. For both types of regression we employ heteroskedasticity-robust standard errors clustered on the firm level. Panel B reports the results for model (7), using a WG regression and a GMM-SYS regression, using in both cases heteroskedasticity-robust standard errors clustered on the firm level, and with the Windmeijer's finite-sample correction for the latter.

The results in Panel A of Table 6 confirm that for cases a.i) and a.ii), for which there is no correlation between P_{it-1} and the explanatory variables, omitting P_{it-1} does not have any impact on the estimation of the coefficients on $BVPS_{it}$ and EPS_{it}, regardless of the estimation method employed (OLS or WG). However, when there is correlation between P_{it-1} and the other explanatory variables, the average bias in the coefficients on $BVPS_{it}$ and EPS_{it} is substantial, and it is stronger for the OLS model than for the WG model. For instance, for case b.i), the average bias for $BVPS_{it}$ is 0.5051 for the OLS model and 0.0985 for the WG model. The size of the bias increases as the autocorrelation coefficient for P_{it} increases: for b.ii) the average bias for $BVPS_{it}$ is 0.7995 for the OLS model and 0.2076 for the WG model. The coefficients on EPS_{it} for these cases are still virtually unbiased, because for these simulations there is no correlation between P_{it-1} and EPS_{it} in the DGP. For cases c.i) and c.ii), on the other hand, the DGP imply a significant correlation between P_{it-1} and both $BVPS_{it}$ and EPS_{it}. As a result, the coefficients on both $BVPS_{it}$ and EPS_{it} are biased, and the bias is larger for the OLS model than for the WG model, and increase when the autocorrelation coefficient for P_{it} increases from 0.8 to 0.9.

The results reported in Panel B of Table 6 show that if P_{it-1} is included, the coefficient on P_{it-1} is biased downwards when using a WG model, and unbiased when using a GMM-SYS model. However, the coefficients on the other explanatory variables are still substantially unbiased for cases a.i) and a.ii). For cases b.i), b.ii), c.i), and c.ii), there is some bias even in the coefficients on $BVPS_{it}$ and EPS_{it} when the WG model is employed, but the size of the bias is negligible, and much lower than for the corresponding cases when P_{it-1} is omitted. For instance, for case b.ii), the average bias for the WG model was 0.2076 in Panel A, but drops to 0.0299 in Panel B. Therefore, even if one does not want to employ dynamic panel data models, including P_{it-1} in the regressions still reduces OVB considerably.

Finally, the results reported in both Panel A and B suggest that choosing the wrong specification may lead to a slightly over-sized or under-sized test. For instance, for Panel A, case a.i), the tests reject the null hypothesis of a coefficient on $BVPS_{it}$ indistinguishable from zero in 8% of the cases for the OLS model for a significance level of 5%, meaning that the test is slightly over-sized, while for EPS_{it} the rejection rate is 4% (slightly under-sized). However, the impact on rejection rates is not as strong as that on the average bias of the coefficients.

[Insert Table 6 Here]

To clarify the impact of autocorrelation on the average bias in the coefficient of variables correlated with stock price, we plot in Figure 3 the average bias in the coefficient on *BVPS* (on the vertical axis) as a function of the autocorrelation coefficient on *P* and *BVPS*, ρ (on the horizontal axis), for three different cases:

- When there is no correlation between *P* and *BVPS*;
- When the coefficient on *BVPS* is 0.2;
- When the coefficient on *BVPS* is 0.4.

The values considered for the autocorrelation coefficient are: ρ = 0.1, 0.3, 0.5, 0.7, and 0.9. The average bias is calculated using 100 replications. Consistent with the results reported in Table 6, the average bias is virtually zero when there is no correlation between *P* and BVPS. When the coefficient on *BVPS* is 0.2 or 0.4, the average bias increases as the autocorrelation coefficient increases. For the same value of the autocorrelation coefficient, ρ, the average bias is larger when the coefficient on *BVPS* is 0.4 than when the coefficient on *BVPS* is 0.2.

[Insert Figure 3 Here]

4.3 Results for the Monte Carlo simulations: Alternative specifications

Table 7, Panel A reports the results for the Monte Carlo simulations for the RRM (model (10)) based for DGP a) and b) as described in section 4.1.[20] We have estimated model (10), using an OLS regression and a WG regression. For both types of regression we employ heteroskedasticity-robust standard errors clustered on the firm level. For DGP a) there should be no relation between market

[20] We deliberately avoid discussing the results for DGP c) for simplicity: for these cases the true coefficients on *DEPS* and $\Delta DEPS$ are different from zero and the high correlation between these two explanatory variables complicates the interpretation of the results.

Rearranging b.i), we obtain: $\frac{P_{it} - P_{it-1}}{P_{it-1}} = RET_{it} = -0.2 + 0.4\frac{BVPS_{it}}{P_{it-1}} + \frac{u_{it}}{P_{it-1}}$.

Rearranging a.i) leads to a similar equation but with a zero coefficient even on $BVPS_{it}/P_{it-1}$.

variables and accounting data, and therefore the coefficients should all be zero.[21] This is because stock price depends only on its own lag for DGP a). For DGP b), stock price should depend only on *BVPS*, not on *EPS* or changes on *EPS*. Therefore, the results shown in the table focus on the rejection rates for cases for which the null hypothesis is true. These rejection rates are much higher (over 40%) than the theoretical ones (5%). To further examine the impact of deflating by the lag of price, in Table 7, Panel B we repeat the simulations after multiplying all variables in model (10) by P_{it-1}. The results show that the rejection rates drop dramatically to values very close to the theoretical ones (5%). It is important to remark that this over-rejection problem does not depend on scale effects due to, for example, different firm size. Therefore, adjustments suggested by previous literature based on including scale proxies as independent variables (Barth and Kallapur, 1996) would not address this issue.

Table 8 reports the results for the Monte Carlo simulations for the PRM deflated by the lag of stock price (model (11)), based on DGP a), b), and c) described in section 4.1. Similar to the results reported in Table 7, the average bias is not substantial, but the rejection rates when the null hypothesis is true are much higher than the theoretical ones, while the rejection rates for the cases for which the null hypothesis is false are well below 100%.

[Insert Tables 7 and 8 Here]

These findings constitute, to the best of our knowledge, the first evidence that adjustments to the PRM implemented in empirical studies to eliminate the impact of scale effects on the validity of rejection rates may in fact lead to over- or under-rejection of the null hypothesis. In other words, the cure may be no better than the disease, and in certain cases may actually be the very cause of the disease.

5. Conclusions

In this study, we have critically evaluated the effects of autocorrelation in the main variables of price level regressions employed in accounting empirical research. We have shown that studies that do not allow for autocorrelation in stock price, book value per share, and earnings per share can caused serious bias in the coefficients of the PRM, a widely-employed specification in market-based accounting research. This bias is strongest for regressions that do not consider firm effects in the regressions. However, adding firm fixed-effects to the specifications does not eliminate the bias.

We have further demonstrated that augmenting the PRM by adding the lag of stock price can reduce the bias. However, to correctly estimate the autocorrelation coefficient, dynamic panel data

[21] By using the DGP a) and b), we calculate RET_{it} considering $DPS_{it} = 0$. Therefore, we are assuming that all firms are non-dividend payers. This is consistent with the simulations in Barth and Clinch (2009).

models must be employed. On the other hand, alternative specifications commonly employed in the empirical accounting literature (such as returns regressions) can lead to further econometric problems: for example, models that use the lag of stock price as a deflator may tend to reject of the null hypothesis of no correlation between market data and accounting data too often when the null hypothesis is true. These results support recent literature cautioning against the use of ratios in applied studies using panel data for variables that may have different stochastic properties (Barghava, 2010).

The importance of our findings extends beyond the scope of market-based accounting studies. Any regression that employs book values of equity or earnings (even if adjusted on a per-share basis) as dependent variable is likely to suffer from omitted variable bias if the regression specification does not allow for the effect of the lags of the dependent variable. Further research is envisaged to assess the impact of omitting autocorrelation of the dependent variable in market-based accounting studies using extended version of the LIM to assess the value relevance of specific accounting items in the financial statements.

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Table 1: Studies on value relevance that employ the PRM (and related modifications).

Paper	Topic	Sample composition and period	Main results
Aly and Hwang (2000)	Value relevance of and country-specific factors.	6,410 firms-year observations from different countries Period: 1986-1995	Value relevance is affected by country-specific factors such as: the type of financial system (bank-oriented vis-à-vis market-oriented), the relevance of private-sector bodies in the standard-setting process, the type of accounting practices (Continental model vis-à-vis British-American model); the relevance of tax rules on financial accounting measurements; and the expenditure on auditing services.
Hung and Subramanyam (2007)	Value Relevance of IAS for a sample of German firms.	80 German listed companies Period: 1998-2002	The adjustment to equity book value is incrementally value relevant under IAS, but the aggregate net income adjustment is not.
Barth et al. (2008)	Adoption of IAS and accounting quality (earnings management, timely loss recognition and value relevance)	327 Listed companies from different countries. Period: 1994-2003	Better value relevance for companies that apply IAS.
Gjerde et al. (2008)	Value relevance of IFRS and of Norwegian GAAP.	145 Norway listed companies Period: 2004-2005	Value-relevance of key IFRS accounting figures not superior to the corresponding local GAAP accounting figures, when they are evaluated unconditionally and conservatively as two independent samples.
Morais and Curto (2009)	Value relevance in European-listed companies after the mandatory application of IAS/IFRS.	6,977 European-listed companies Period: 2000-2005	Increasing value relevance of accounting data with the mandatory adoption of IAS/IFRS. Value relevance of accounting information under IAS/IFRS is different between countries.

Table 1 continued			
Aharony et al (2010)	Value relevance of accounting numbers in Europe after the mandatory adoption of the IFRS.	2,298 European-listed companies Period: 2004-2005	Increasing value relevance for investors in equity securities in the EU of the three accounting numbers (goodwill, R&R expenses, and asset revaluation) with the adoption of the IFRS
Devalle et al. (2010)	Value relevance of accounting information in Europe after the mandatory adoption of the IFRS	3,721 European-listed companies Period: 2002-2007	Improvement in value relevance in the post IFRS period, with heterogeneous effects for the book value per share and the earnings per share.
Horton and Serafeim (2010)	Value-relevance of information contained in IFRS reconciliation adjustments with UK GAAP.	297 UK listed companies Period: 2002-2007	Coefficient on the aggregate net income adjustment is significantly positive. Net income adjustments are value relevant.
Agostino et al. (2011)	Value relevance of accounting information in the European banking industry before and after the adoption of IFRS	221 European listed banks Period: 2000-2006	Increasing value relevance of earnings after compulsory adoption of IFRS.
Barth et al. (2012)	Comparability of value relevance between IFRS and U.S. GAAP.	3,400 Listed companies from different countries Period: 1995-2006	IFRS lead to higher value relevance comparability with U.S. GAAP than non-U.S. national GAAP.
Barth et al. (2014)	Value relevance of reconciliation adjustments for net income and book value adjustments to IFRS.	1,201 European-listed companies Period: 2005	The adjustments to net income resulting from mandatory adoption of IFRS in Europe in 2005 are value relevant. The net income adjustment relating to IAS 39 is value relevant for financial firms but not for non-financial firms.

Table 2: First-order autocorrelation coefficients for *P*, *P**, *BVPS*, and *EPS* for a sample of European firms.

	P	*P**	*BVPS*	*EPS*		*P*	*P**	*BVPS*	*EPS*
All countries	0.9820	0.9841	0.9818	0.9148					
					Italy	0.8797	0.9779	0.9845	0.8435
Austria	0.9691	0.9706	0.9962	0.9148	Lux.burg	0.8253	0.9167	0.4865	0.6805
Belgium	0.9838	0.9828	0.9961	0.6402	Neth.nds	0.9624	0.9265	0.9830	0.9970
Denmark	0.9649	0.9646	0.9981	0.8069	Norway	0.9544	0.9767	0.9805	0.7897
Finland	0.9509	0.9822	0.9679	0.9575	Portugal	0.8758	0.9844	0.9903	0.8535
France	0.9633	0.9618	0.9113	0.9728	Spain	0.9054	0.9503	0.9665	0.9053
Germany	0.9765	0.9674	0.9975	0.6019	Sweden	0.8837	0.8862	0.8907	0.5874
Greece	0.9362	0.9946	0.9933	0.9189	Switz.nd	0.9875	0.9875	0.9838	0.9594
Ireland	0.8983	0.9917	0.9609	0.7537	UK	0.7674	0.9952	0.9773	0.7770

Note: For all cases the autocorrelation is significant at the 5% level.

Table 3: Correlation between first lag of stock price (*P* and *P**) and *BVPS*, *EPS* for a sample of European firms.

	BVPS	*EPS*	*BVPS*	*EPS*		*BVPS*	*EPS*	*BVPS*	*EPS*
	Lag of P		*Lag of P**			*Lag of P*		*Lag of P**	
All countries	0.5892	0.6852	0.5608	0.6512					
					Italy	0.4779	0.4183	0.2487	0.2381
Austria	0.8236	0.6076	0.8085	0.6060	Lux.burg	0.0373^{+}	-0.0487^{+}	-0.0857^{+}	-0.1155^{+}
Belgium	0.9558	0.8234	0.9408	0.7972	Neth.nds	0.9669	0.9717	0.2919	0.5089
Denmark	0.9116	0.9122	0.8985	0.8987	Norway	0.9524	0.6505	0.6331	0.4327
Finland	0.9549	0.9239	0.5112	0.5218	Portugal	0.5316	0.5580	-0.0865^{+}	-0.1547
France	0.7794	0.5147	0.7774	0.5134	Spain	0.6371	0.2666	0.4475	0.2216
Germany	0.2271	0.1869	0.1654	0.1514	Sweden	0.7272	0.8920	0.7150	0.8792
Greece	0.8628	0.8617	0.1513	0.1505	Switz.nd	0.9542	0.9671	0.9538	0.9670
Ireland	0.7201	0.8148	0.1309^{+}	0.2075	UK	07775	0.7895	0.1689	0.1328

Note: For all cases except those denoted by "$^{+}$" the correlation is significant at the 5% level.

Table 4. PRM Regressions using a sample of European firms.

Dep. var: P	OLS	WG	WG	*Dep. var: P**	OLS	WG	WG
Lag of P	–	–	0.7775***	*Lag of P**	–	–	0.8688***
			(0.1070)				(0.0709)
BVPS	-0.1511	1.5258***	0.8101***	*BVPS*	-0.1592	1.5409***	0.7519***
	(0.5847)	(0.4273)	(0.2480)		(0.5867)	(0.4378)	(0.2572)
EPS	10.5345*	1.4700	-0.0260	*EPS*	10.1024	1.4535	-0.3312
	(6.3421)	(1.1748)	(0.5357)		(7.5106)	(1.1751)	(0.4425)
Constant	20.2931	-15.9407	-21.3678**	Constant	-34.1626	-74.0945***	-29.5740**
	(21.7915)	(25.9035)	(10.5356)		(21.0808)	(25.7110)	(11.4820)
Observations	14,943	14,943	14,943	Observations	14,908	14,908	14,908
Number of firms	2,814	2,814	2,814	Number of firms	2,801	2,801	2,801

Notes: *** Denotes significance at the 1% level. ** Denotes significance at the 5% level. * Denotes significance at the 10% level.

Table 5. PRM regressions: P-values for Hausman test for WG and RE for a sample of European firms. Dependent variables: *P* and *P**.

	P	*P**		*P*	*P**
All countries	0.0000	0.0000			
			Italy	0.0000	0.0000
Austria	0.0057	0.0054	Lux.burg	0.3091	0.3099
Belgium	0.0000	0.0000	Neth.nds	0.0000	0.0000
Denmark	0.0000	0.0000	Norway	0.0000	0.0000
Finland	0.0000	0.0000	Portugal	0.0002	0.0000
France	0.0000	0.0000	Spain	0.0000	0.0000
Germany	0.0000	0.0000	Sweden	0.0000	0.0000
Greece	0.0000	0.0000	Switz.nd	0.0000	0.0000
Ireland	0.0000	0.0000	UK	0.0000	0.0000

Table 6. Monte Carlo simulations results for DGP a), b), and c) based on 500 replications using simulated data for 2,000 firms and 10 years.

Panel A: Estimation of model (6) using a pooled OLS regression and a WG regression.

Dep. var.: P_{it}			**OLS**		**WG**	
DGP	*Variable*	*True coefficient*	*Average bias*	*Rejection rate (α=5%)*	*Average bias*	*Rejection rate (α=5%)*
a.i)	P_{it-1}	0.8	-	-	-	-
	$BVPS_{it}$	0.0	0.0002	8.00%	-0.0006	5.80%
	EPS_{it}	0.0	0.0003	4.80%	0.0002	5.00%
a.ii)	P_{it-1}	0.9	-	-	-	-
	$BVPS_{it}$	0.0	0.0004	8.00%	-0.0004	6.40%
	EPS_{it}	0.0	0.0003	4.00%	0.0002	5.20%
b.i)	P_{it-1}	0.8	-	-	-	-
	$BVPS_{it}$	0.4	0.5051	100%	0.0985	100%
	EPS_{it}	0.0	-0.0006	5.00%	0.0003	7.80%
b.ii)	P_{it-1}	0.9	-	-	-	-
	$BVPS_{it}$	0.4	0.7995	100%	0.2076	100%
	EPS_{it}	0.0	-0.0009	5.80%	0.0002	6.60%
c.i)	P_{it-1}	0.8	-	-	-	-
	$BVPS_{it}$	0.4	0.5049	100%	0.0992	100%
	EPS_{it}	0.2	0.2525	100%	0.0498	100%
c.ii)	P_{it-1}	0.9	-	-	-	-
	$BVPS_{it}$	0.4	0.7989	100%	0.2088	100%
	EPS_{it}	0.2	0.3996	100%	0.1041	100%

Notes: For consistency between model (6) and (7), we exclude observations for which the lag of *P* is missing for model (6). Therefore, for each regression we lose 2,000 observations, and the total number of observations is 18,000 (20,000 – 2,000). Both the OLS and the WG regressions employ heteroskedasticity-robust standard errors clustered on the firm level. Rejection rates are based on the proportion of the 500 replications for which the t-statistic is larger than |1.96|.

Table 6. Monte Carlo simulations results for DGP a), b), and c) based on 500 replications using simulated data for 2,000 firms and 10 years.

Panel B: Estimation of model (7) using a WG regression and a GMM-SYS regression.

Dep. var.: P_{it}			**WG**		**GMM-SYS**	
DGP	*Variable*	*True coefficient*	*Average bias*	*Rejection rate (α=5%)*	*Average bias*	*Rejection rate (α=5%)*
a.i)	P_{it-1}	0.8	-0.2717	100%	0.0000	100%
	$BVPS_{it}$	0.0	-0.0006	7.20%	-0.0001	5.40%
	EPS_{it}	0.0	0.0004	6.40%	0.0005	5.80%
a.ii)	P_{it-1}	0.9	-0.3024	100%	0.0000	100%
	$BVPS_{it}$	0.0	-0.0005	7.00%	-0.0001	4.80%
	EPS_{it}	0.0	0.0004	6.20%	0.0004	6.40%
b.i)	P_{it-1}	0.8	-0.1643	100%	0.0005	100%
	$BVPS_{it}$	0.4	0.0205	100%	-0.0008	100%
	EPS_{it}	0.0	0.0002	4.00%	-0.0003	5.80%
b.ii)	P_{it-1}	0.9	-0.1279	100%	0.0003	100%
	$BVPS_{it}$	0.4	0.0299	100%	-0.0007	100%
	EPS_{it}	0.0	0.0002	4.00%	-0.0002	5.80%
c.i)	P_{it-1}	0.8	-0.1443	100%	0.0004	100%
	$BVPS_{it}$	0.4	0.0177	100%	-0.0014	100%
	EPS_{it}	0.2	0.0092	100%	-0.0004	100%
c.ii)	P_{it-1}	0.9	-0.1107	100%	0.0003	100%
	$BVPS_{it}$	0.4	0.0255	100%	-0.0012	100%
	EPS_{it}	0.2	0.0129	100%	-0.0004	100%

Notes: For consistency between model (6) and (7), we exclude observations for which the lag of *P* is missing for model (6). Therefore, for each regression we lose 2,000 observations, and the total number of observations is 18,000 (20,000 – 2,000). The WG regressions employ heteroskedasticity-robust standard errors clustered on the firm level, and the GMM-SYS regressions employ Windmeijer's finite-sample correction. Rejection rates are based on the proportion of the 500 replications for which the t-statistic is larger than |1.96|.

Table 7. RRM: Monte Carlo simulations results for OLS and WG regressions.

Panel A: Estimation of model (10).

Dep. var.: RET_{it}			**OLS**		**WG**	
DGP	*Variable*	*True coefficient*	*Average bias*	*Rejection rate (α=5%)*	*Average bias*	*Rejection rate (α=5%)*
a.i)	$DEPS_{it}$	0.0	0.0189	47.40%	0.0191	47.40%
	$\Delta DEPS_{it}$	0.0	-0.0130	48.20%	-0.0132	48.20%
a.ii)	$DEPS_{it}$	0.0	0.0265	40.40%	0.0266	40.20%
	$\Delta DEPS_{it}$	0.0	-0.0597	45.80%	-0.0596	46.20%
b.i)	$DEPS_{it}$	0.0	0.0255	46.00%	0.0254	46.00%
	$\Delta DEPS_{it}$	0.0	-0.0256	46.40%	-0.0254	46.40%
b.ii)	$DEPS_{it}$	0.0	0.0096	48.60%	0.0095	48.40%
	$\Delta DEPS_{it}$	0.0	0.0010	44.60%	0.0010	44.60%

Panel B: Estimation of model (10) after multiplying *RET*, *DEPS*, and Δ*DEPS* by P_{it-1}.

Dep. var.: ΔP_{it} ($P_{it} - P_{it-1}$)			**OLS**		**WG**	
DGP	*Variable*	*True coefficient*	*Average bias*	*Rejection rate (α=5%)*	*Average bias*	*Rejection rate (α=5%)*
a.i)	EPS_{it}	0.0	0.0004	5.60%	0.0007	5.20%
	ΔEPS_{it}	0.0	0.0000	5.20%	-0.0001	4.80%
a.ii)	EPS_{it}	0.0	0.0003	3.40%	0.0006	5.40%
	ΔEPS_{it}	0.0	0.0001	5.40%	-0.0001	4.80%
b.i)	EPS_{it}	0.0	0.0001	7.40%	0.0003	4.40%
	ΔEPS_{it}	0.0	-0.0002	6.00%	-0.0004	5.80%
b.ii)	EPS_{it}	0.0	0.0001	6.40%	0.0004	4.60%
	ΔEPS_{it}	0.0	-0.0002	5.60%	-0.0004	6.40%

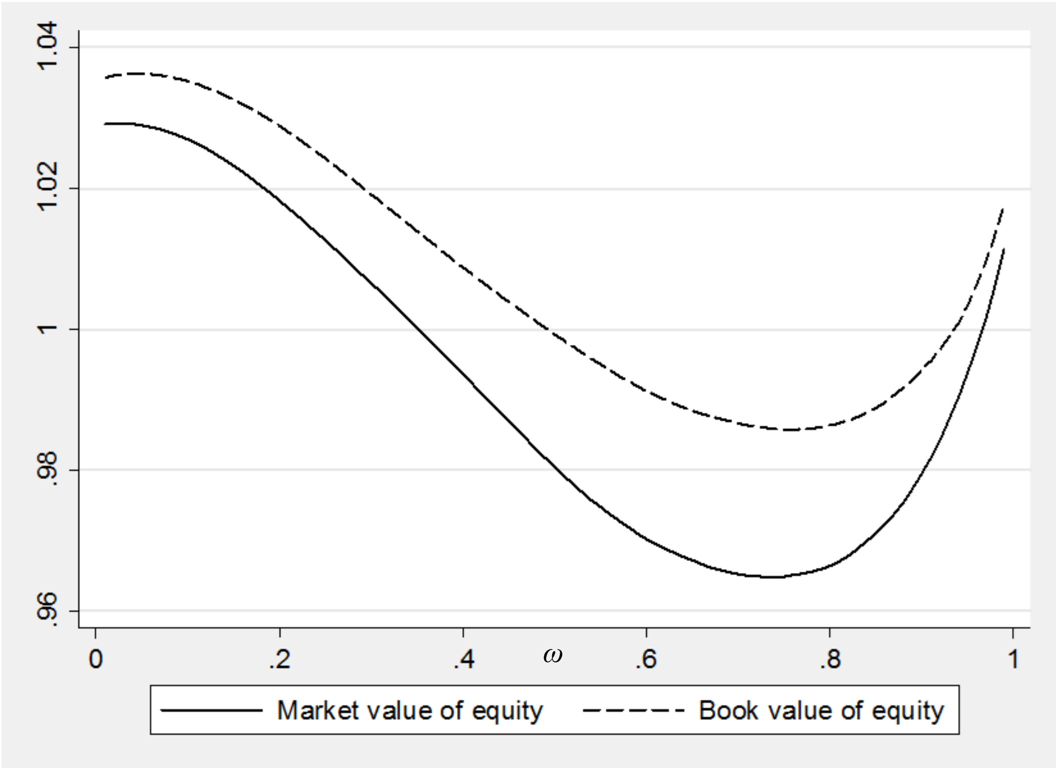
Notes: We assume DGP a) and b) and employ 500 replications using simulated data for 2,000 firms and 10 years. Both the OLS and the WG regressions use heteroskedasticity-robust standard errors clustered on the firm level. $DEPS_{it} = EPS_{it}/P_{it-1}$ and $\Delta DEPS_{it} = \Delta EPS_{it}/P_{it-1}$. Rejection rates are based on the proportion of the 500 replications for which the t-statistic is larger than |1.96|.

Table 8. PRM deflated: Monte Carlo simulations results. Estimation of model (11) using a pooled OLS regression and a WG regression.

Dep. var.: P_{it}/P_{it-1}			**OLS**		**WG**	
DGP	*Variable*	*True coefficient*	*Average bias*	*Rejection rate (α=5%)*	*Average bias*	*Rejection rate (α=5%)*
a.i)	$DBVPS_{it}$	0.0	0.0389	43.00%	0.0388	43.20%
	$DEPS_{it}$	0.0	-0.0126	47.40%	-0.0128	47.60%
a.ii)	$DBVPS_{it}$	0.0	0.0124	47.20%	0.0123	47.20%
	$DEPS_{it}$	0.0	0.0085	42.40%	0.0085	42.40%
b.i)	$DBVPS_{it}$	0.4	-0.0285	67.60%	-0.0286	67.60%
	$DEPS_{it}$	0.0	0.0129	48.60%	0.0131	48.40%
b.ii)	$DBVPS_{it}$	0.4	-0.0362	65.60%	-0.0362	65.60%
	$DEPS_{it}$	0.0	0.0008	45.20%	0.0007	45.20%
c.i)	$DBVPS_{it}$	0.4	-0.0395	64.40%	-0.0396	64.40%
	$DEPS_{it}$	0.2	-0.0765	51.20%	-0.0767	51.40%
c.ii)	$DBVPS_{it}$	0.4	0.0017	69.60%	0.0018	69.60%
	$DEPS_{it}$	0.2	0.0241	54.00%	0.0240	54.20%

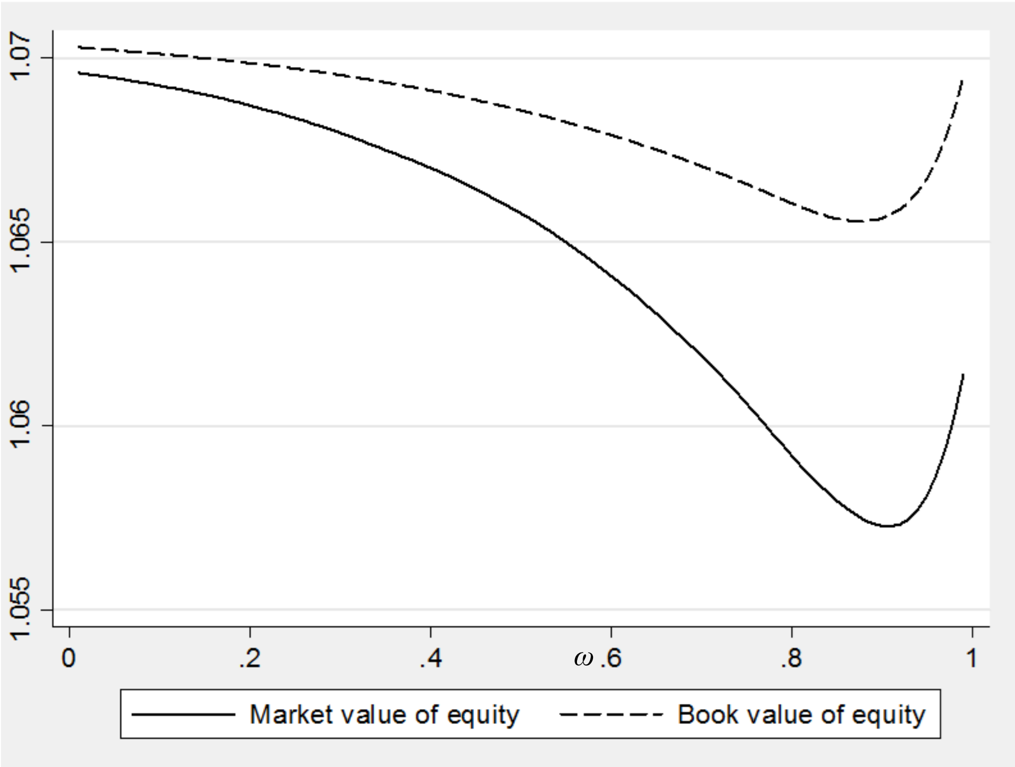
Notes: Similar to Table 6, we assume DGP a), b), and c) and employ 500 replications using simulated data for 2,000 firms and 10 years. Both the OLS and the WG regressions use heteroskedasticity-robust standard errors clustered on the firm level. $DBVPS_{it} = BVPS_{it}/P_{it-1}$ and $DEPS_{it} = EPS_{it}/P_{it-1}$. Rejection rates are based on the proportion of the 500 replications for which the t-statistic is larger than |1.96|.

Figure 1. Autocorrelation coefficients in book value of equity and market value of equity as a function of ω (moderation period).



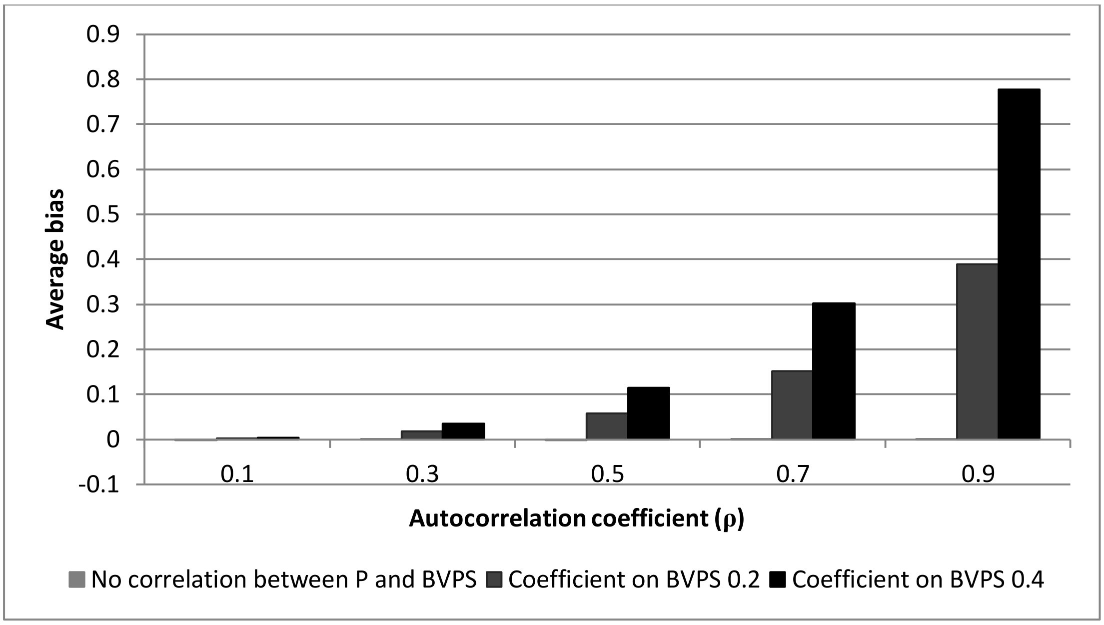
Note: the starting value for interest rates is 3%.

Figure 2. Autocorrelation coefficients in book value of equity and market value of equity as a function of ω (growth period).



Note: the starting value for interest rates is 12%.

Figure 3. Autocorrelation and bias of the coefficients.



Note: the average bias is calculated on the basis of 2,000 fictitious firms and 10 years. We simulate 100 series for *P* and *BVPS*. The DGP for *P* and *BVPS* is as follows:

- $P_{it} = \rho\, P_{it-1} + u_{it}$ and $BVPS_{it} = \rho\, BVPS_{it-1} + u_{it}$
- $P_{it} = \rho\, P_{it-1} + 0.2\, BVPS_{it} + u_{it}$ and $BVPS_{it} = \rho\, BVPS_{it-1} + u_{it}$
- $P_{it} = \rho\, P_{it-1} + 0.4\, BVPS_{it} + u_{it}$ and $BVPS_{it} = \rho\, BVPS_{it-1} + u_{it}$

The autocorrelation coefficient, ρ, takes on the following values: 0.1, 0.3, 0.5, 0.7, and 0.9.

Appendix

A1. Generating book value of equity and market value of equity using the Ohlson model

We simulate data for 500 fictitious firms and 40 years of data. We set the starting value for the book value of equity at 100. The starting value for $R = (1 + r)$ is 1.03 for the moderation period (Figure 1) and 1.12 for the growth period (Figure 2). For the subsequent periods, R follows a random walk with normally distributed and independent innovations with mean zero and standard deviation equal to 0.005. The abnormal earnings follow an AR(1) process according to equation (3), with $\gamma = 0.2$ and $\omega = 0.01, 0.02, \ldots, 1$. The two error terms are generated assuming: $\varepsilon_{1,t} \sim N(0, \sigma^2_{\varepsilon 1})$ and $\varepsilon_{2,t} \sim N(0, \sigma^2_{\varepsilon 2})$, with $\varepsilon_{1,t} = \varepsilon_{2,t}$ and $\sigma^2_{\varepsilon 1} + \sigma^2_{\varepsilon 2} = 102.2^2 R^{-40}$ (Barth and Clinch, 2009). Dividends are assumed to be zero. Following Ohlson (1995), we also assume $m = 0$.

A2. Dynamic panel models

The equations in first-differences can be written as:

$$\Delta P_{it} = \rho \Delta P_{it-1} + b\Delta BVPS_{it} + c\Delta EPS_{it} + \Delta\varphi_{it} \quad \text{(A1)}$$

The matrix of instruments for ΔP_{it-1} is constructed for each time period starting from P_{it-2}, and substituting missing values with zeros:

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \cdots \\ P_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots \\ 0 & P_{i2} & P_{i1} & 0 & 0 & 0 & \cdots \\ 0 & 0 & 0 & P_{i3} & P_{i2} & P_{i1} & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \quad \text{(A2)}$$

The instruments for the levels equation employ only one lag for each time period and instrumental variable because using more lags would be redundant:

$$\begin{bmatrix} 0 & 0 & 0 & \cdots \\ \Delta P_{i2} & 0 & 0 & \cdots \\ 0 & \Delta P_{i3} & 0 & \cdots \\ 0 & 0 & \Delta P_{i4} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \quad \text{(A3)}$$

Therefore, the instruments for the differenced and levels equations are, respectively:[22]

[22] Several problems may arise when employing the GMM-DIF or GMM-SYS in actual datasets. First, for unbalanced panels, first-differencing exacerbates the problem of missing observations. However, this problem can be addressed using orthogonal deviations (Arellano and Bover, 1995), an option available for "xtabond2". A second issue arises with GMM-SYS, for which the number of instruments is quartic in T. The large number of instruments can weaken the validity of the test for over-identifying restrictions (that is, the Hansen test in case of heteroskedastic errors), leading to a very large p-value. This problem, commonly referred to as "instruments proliferation", can be addressed via the "collapsing technique" (Roodman, 2009), also available as an option for "xtabond2".

$$\mathrm{E}\left[P_{it-l}\Delta\varepsilon_{it}\right]=0 \qquad \text{for each } t \geq 3 \text{ and } l \geq 2 \tag{A4}$$

$$\mathrm{E}\left[\Delta P_{it-1}\varepsilon_{it}\right]=0 \qquad \text{for each } t \geq 3 \tag{A5}$$