Do women on corporate boards influence corporate social performance? A control function approach

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ABSTRACT

We examine if women on corporate boards (WOCB) influence a firm's corporate social performance (CSP). To do this, we utilize stakeholder theory. From an empirical standpoint, we use the control function (CF) approach suggested by Wooldridge (2015), which takes into account the issue of endogeneity raised in the literature (namely, omitted variables, reverse causality, and dynamic endogeneity). Using a sample of firms from the S&P 500 between 2004 and 2015, we find that WOCB have a positive and significant effect (at the 5% level) on CSP. We compare our results to more traditional approaches (pooled OLS, the fixed-effects model, and system GMM). We shed light on an issue that is still considered controversial (Byron and Post, 2016).

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1. Introduction

Challenges such as climate change, poor working conditions, and corporate scandals have led firms to take account of corporate social responsibility (CSR) issues in their own business (e.g. Ioannou and Serafeim, 2012). Corporate social performance (CSP) refers to a "business organization's configuration of principles of social responsibility, processes of social responsiveness, and policies, programs and observable outcomes as they relate to the firm's societal relationships" (Wood, 1991, p. 693). Accordingly, an organization's CSP represents its performance in terms of CSR (Hill et al., 2007, McWilliams and Siegel, 2001). Board of directors (BoD) – and corporate governance (CG) scholars – have considered ways to increase CSP. Women on corporate boards (WOCB) are one of the solutions considered in the literature (Byron and Post, 2016) and by professionals (e.g. Catalyst, 2011)[2]. Therefore, to what extent WOCB influence CSP is a topical issue.

To date, few studies have examined the relationship between WOCB and CSP (e.g. Boulouta, 2013), focusing instead primarily on the relationship with financial performance focusing primarily on financial performance (FP) (Post and Byron, 2015). Furthermore, existing empirical studies have yielded mixed results. Two recent works, Francoeur et al. (2019) and Wasiuzzaman and Wan Mohammad (2020), document a positive relationship between WOCB and CSP, whereas other studies have found a negative (e.g. Husted and de Sousa-Filho, 2019, Zahid et al., 2020) or null relationship (e.g. Boulouta, 2013, Manita et al., 2018).

Many factors could explain the mixed results: for example, the use of different samples, time windows, and empirical methods (Adams et al., 2015). We argue that three sources of endogeneity (omitted/unobserved firm characteristics, reverse causality, and dynamic endogeneity) may bias the WOCB–CSP relationship. Not addressing this issue may induce erroneous inferences (Wintoki et al., 2012). The contribution of this article is to address the endogeneity issue by using the control function (CF) approach suggested by Wooldridge (2015), in combination with a correlated random effect (CRE) approach by combining a correlated random effect (CRE) approach (Chamberlain, 1984, Mundlak, 1978) to address the endogeneity issue.

The purpose of this article is, therefore, to provide new evidence regarding the relationship between WOCB and CSP and we use stakeholder theory and the CF approach to do so.

[2] Catalyst, 2011. Gender and corporate social responsibility: It's a matter of sustainability.

2. Literature review

Agency (Fama and Jensen, 1983, Jensen and Meckling, 1976) and resource-dependence (Pfeffer, 1972, Pfeffer and Salancik, 1978) theories are the two theoretical frameworks most used in the literature to examine the two key functions of the BoD (Hillman and Dalziel, 2003): monitoring management and providing resources. However, we adopt another theoretical framework by following Hill and Jones (1992), who assigned a third function to the BoD: increasing the firm's sustainable behavior and accountability to stakeholders. Stakeholder theory (Donaldson and Preston, 1995, Freeman, 1984) postulates that organizations' success depends on how stakeholders' expectations are taken into account, such as by respecting social values or the effectiveness of the responses to those expectations.

According to Huse and Solberg (2006), WOCB are highly involved and committed to their task, owing, among other factors, to their (more) participative, democratic, or communal leadership styles (Eagly et al., 2003). The approaches they bring to the boardroom are argued to be conducive to significant improvement in the board's decision making or monitoring, which is often a prelude to the firm's commitment to CSR activities (Ben-Amar et al., 2017, Mallin et al., 2013).

Since WOCB tend to respond to different norms, attitudes, beliefs, and perspectives (Pelled et al., 1999), they are more sensitive in guiding CSR activities with regard to their intensity and scope (Bear et al., 2010). Galbreath (2011) adds that WOCB tend to favor long-term sustainability projects. Accordingly, WOCB are more likely to fund, select, and support CSR projects.

In sum, Jensen (2001) suggests the need for firms to establish lasting relationships with stakeholders to maximize shareholder/stakeholder value. Michelon and Parbonetti (2012) consider that good CG and CSR are complementary mechanisms for better considering stakeholders' expectations. By virtue of their sensitivity to environmental and societal issues (Ben-Amar et al., 2017, Hafsi and Turgut, 2013), WOCB are, therefore, more inclined to influence CSR and thus CSP (Nielsen and Huse, 2010).

3. Methods

The initial study sample included all the companies that made up the S&P 500 as of December 31, 2015 and covers the period from 2004 to 2015. Financial and utility firms (because of their specificities) and companies missing data were excluded from the sample. The final sample consisted of 369 firms and 3,236 firm-year observations.

Following Nollet et al. (2016) and Buchanan et al. (2018), CSP is approached through the Bloomberg ESG disclosure score. Bloomberg assigns E (Environmental), S (Societal), and G (Governance) scores on data points collected via public sources (e.g. annual reports or CSR reports). These data points are based on the Global Reporting Initiative's (GRI) *Sustainability Reporting Guidelines*, which is the most widely used framework for the voluntary reporting of environmental and social performance (Eccles et al., 2011). The score regarding disclosure of ESG information ranges from 0 (minimum) to 100 (maximum). Consequently, the Bloomberg scores reflect both a firm's CSR policy and its performance (Buchanan et al., 2018, Nollet et al., 2016).

Following Reguera-Alvarado et al. (2017), we use the firm's visibility as our instrumental variable. Since there is no fine measurement of visibility, we operationalize this by using a dummy variable (*F100*) that equals 1 if a firm belongs, in a given year, to the S&P 100 index. This index encompasses the largest companies in the US. We hypothesize that these firms are expected to be under scrutiny from stakeholders (investors, the media, etc.) to have more WOCB representation (Hillman et al., 2007).

To save space, Table 1 provides an overview of the variables and their definitions as they are commonly used in the literature (e.g. Boulouta, 2013, Francoeur et al., 2019).

[Place Table 1 here]

Our model is as follows:

$$(\mathrm{FP})_{it} = \rho\ (\mathrm{FP})_{it-1} + \beta\ (\mathrm{WOCB})_{it} + (\mathrm{CV})'_{it}\ \Upsilon + (\mathrm{YEAR})_{t} + (\mathrm{FE\ effect})_{i} + \varepsilon_{it} \quad \textbf{[1]}$$

where *i* denotes firms in the sample; *t* refers to time period; and *CV* refers to control variables. We include *year dummies* and *FE effect* to capture unobservable time-varying factors and unobservable time-invariant firm heterogeneity.

The relationship between CSP and WOCB is generally affected by an endogeneity issue (Adams, 2016). In any specific situation, many firm-specific variables are sometimes difficult to observe or measure, and so are usually omitted (Boulouta, 2013).

Reverse causality might be another source of endogeneity. Specifically, WOCB may affect CSP, but it is also possible that more socially responsible firms may be more likely to appoint female directors (Boulouta, 2013). Consequently, the direction of causality could go both ways (Adams, 2016).

Wintoki et al. (2012) argue that any corporate financial decisions are likely to be dynamic in nature. That is, past action may be a proxy for some unobservable firm attributes that influence current action. Accordingly, a firm's contemporaneous FP and governance characteristics might be influenced by its past FP. This thereby creates another source of endogeneity in the CG–performance nexus: dynamic endogeneity (Wintoki et al., 2012).

Modeling the present performance of a firm as a function of its past performance, introducing an FE estimator to capture unobserved time-invariant firm heterogeneity, as assumed in Eq. [1], results in a potential correlation between the unobserved FE and the lagged value of the performance index, or, *a fortiori*, between the unobserved FE and the initial value of the performance index. This problem is called the "initial condition problem" (Heckman, 1981). Thus, applying ordinary least squares (OLS) to Eq. [1] can be shown to be inconsistent.

Existing studies use the FE panel estimator to mitigate endogeneity. However, the FE estimator is not designed to deal with an initial condition problem. Nickell (1981) shows that the FE estimator produces an inconsistent estimation of the effect of past performance on present performance. The problem is that the transformed lagged performance measure is now correlated with the transformed error (Verbeek, 2012).

The availability of external instruments enables us to define an alternative strategy to examine the relationship between WOCB and CSP based on recent developments in CRE and CF approaches (Wooldridge, 2015). In essence, Wooldridge (2010) defines CF as the use of a proxy variable that renders an endogenous explanatory variable exogenous (when conditioned) in a regression. As shown in the Appendix, the combination of these two techniques makes it possible to deal with the three issues previously mentioned. Potential correlation between firm characteristics and some control variables and the initial condition problem can be addressed using CRE, and CF provides an explicit treatment of endogenous explanatory variables. An estimation strategy proceeds in two steps using only pooled OLS and robust *t*-statistics when assessing the validity of external instruments by rank condition test or the endogeneity of the WOCB measure.

Accordingly, the empirical Eq. of [1] is given by:

$$(FP)_{it} = \rho\,(FP)_{it-1} + \beta\,(WOCB)_{it} + \Upsilon_1\,(FSIZE)_{it} + \Upsilon_2\,(ROA)_{it} + \Upsilon_3\,(LEV)_{it} + \Upsilon_4\,(R\&D)_{it} + \Upsilon_5\,(BINDEP)_{it} + (YEAR)_t + (FE\ effect)_i + \varepsilon_{it} \quad [2]$$

4. Results

Table 2 shows the descriptive statistics and correlations. The mean (median) CSP is 28.45 (23.97) – vs. 25.15 for Nollet et al. (2016) – suggesting that CSP has improved in recent years. The mean (median) percentage of WOCB is 16.00% (9.4%) vs. 18% (8.0%) for Francoeur et al. (2019). The later time period in Francoeur et al. may explain the difference.

Multicollinearity had little impact on our analyses: there was no value > 0.70 (in absolute value) or variance inflation factors (VIF) < 10 (Wooldridge, 2014).

[Place Table 2 here]

Table 3 presents our results, including, for comparison, the results for OLS, FE and the generalized method of moments (GMM), because these methods are commonly used in the literature.

For all the models (except model 1), we find that the coefficient of past CSP is positively and significantly (at the 1% level) correlated with current CSP, supporting Wintoki et al.'s (2012) claim that performance is path-dependent.

Model 1 shows WOCB are positively and significantly (at the 5% level) correlated to CSP, which is consistent with Hafsi and Turgut (2013) and Wasiuzzaman and Wan Mohammad (2020).

When time-invariant unobserved heterogeneity is considered through firm FE, the coefficient for WOCB is no longer significant at the 10% level (model 2), which is consistent with Hussain et al. (2018) and Manita et al. (2018).

In model 3, we used the two-step system GMM estimator (Boulouta, 2013, Francoeur et al., 2019). Internal instruments were collapsed to avoid their proliferation (Roodman, 2009). The coefficient for WOCB in model 3 is not significantly correlated to CSP (at the 10% level), which is consistent with Boulouta (2013) but different from Francoeur et al. (2019). The Hansen *J*-test yields a *p*-value of 0.10, implying the instruments' validity.

Model 6 presents the results of the estimation of the auxiliary regression (see Appendix): our instrument is positively and significantly (at the 1% level) correlated to WOCB; the *p*-values of the rank condition test are very small and *F100* has the expected sign, suggesting that our model makes theoretical sense (Reguera-Alvarado et al., 2017). Consequently, our instrument is considered to be valid (Baum, 2006). Models 4 and 5 show that WOCB must be considered endogenous because an estimated first-step residual appears to be significantly different from zero using a bootstrapped robust standard error. Accordingly, the estimated coefficient of WOCB is positively and significantly correlated to CSP, but at the 10% significance level.

[Place Table 3 here]

5. Conclusion

Unlike the existing literature examining the WOCB–CSP relationship from a static perspective, we analyzed this relationship in a dynamic framework. By considering dynamic endogeneity and the other two sources of endogeneity, we would expect to provide reliable inferences (Wintoki et al., 2012). We are responding to the calls from Flannery and Hankins (2013) and Zhou et al. (2014) to use dynamic models in corporate finance and CG research. Hence, using a sample of S&P firms over the period 2004–2015 and after controlling the sources of endogeneity, we find that the WOCB–CSP relationship is weak, since the level of significance is only 10%, suggesting that WOCB do not significantly influence CSP despite the theoretical arguments. Is this a surprising result? Perhaps not, as Adams and Ferreira (2009) already argued that when endogeneity is properly considered in the WOCB–FP relationship, WOCB has a negative or possibly neutral effect on FP. Overall, our findings are consistent with the CG literature (e.g. Nguyen et al., 2015, Sila et al., 2016) that argues that board composition generally has little impact on a firm's outcomes when endogeneity (omitted/unobserved firm characteristics, reverse causality, and dynamic endogeneity) is controlled.

Following Wintoki et al. (2012), we argue that the existing empirical literature is probably plagued by serious endogeneity issues. The mixed results in models 1 and 2 of Table 3 – using traditional OLS and FE methods, respectively – are probably the outcomes of a failure to consider endogeneity issues (omitted/unobserved firm characteristics and reverse causality). Moreover, Roberts and Whited (2013) argue that inference is virtually impossible due to biased and inconsistent parameters. Similarly, model 3 yields a different result to Francoeur et al. (2019). We argue that not considering dynamic endogeneity can bias result. In almost all of our models, past CSP is found to be statistically significant (at the 1% level), supporting Wintoki et al.'s (2012) claim that performance is path-dependent, i.e. past performance is correlated to current performance. Accordingly, many existing empirical results should be considered with caution.

In this article, we propose an alternative method to examine the WOCB–CSP relationship: the CF approach. One advantage is the simple re-specification of the model through the introduction of new regressors controlling for endogenous explanatory variables, and the computational tractability this specification yields (Wooldridge, 2015). We argue that CF provides a useful alternative to the GMM approach. Indeed, Roodman (2009) argues that GMM works "under arguably special circumstances" (p. 156), i.e. in the case of the nonproliferation of instruments. This creates some asymptotic results for GMM estimators, rendering specification tests misleading. Estimated variances of coefficients and the Hansen *J*-test can be too small, leading to overfitting of lagged dependent variables and too much confidence in the validity of internal instruments. Consequently, the GMM approach might have some limitations. The CF approach is a credible alternative.

One implication of our work is that the appointment of WOCB should not be based on the sole criterion of performance (Carter et al., 2010), as there is no evidence of a strong relationship between WOCB and CSP. In addition, our evidence neither supports nor rejects the effectiveness of board gender quota implementations (Greene et al., 2020). Our findings may, however, be valuable to governments, stakeholders, and fund managers, as we do not find that WOCB are detrimental to CSP.

Our study has some limitations. First, we focus on the largest US listed companies. Further studies are needed on small- and medium-sized firms, since they are significantly different, especially regarding gender diversity and FP. Second, we examined the US context. However, Grosvold and Brammer (2011) argue that CG systems play a significant role in female representation on boards. Hence, further cross-country studies seem necessary to confirm or reject our findings.

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Table 1
Definition of variables

Variable	**Definition**
WOCB	The number of female directors divided by the total number of directors
Firm size	The natural logarithm of total assets (*FSIZE*)
Firm performance	Income before depreciation divided by total assets (return on assets, *ROA*)
Leverage	The ratio of total debt to total assets (*LEV*)
R&D	Research and development divided by sales (*R&D*)
Board independence	The proportion of outside – non-executive – directors on the board (*BINDEP*)

This table defines the variables used in the empirical analysis. The source of the data is Bloomberg.

Table 2
Descriptive statistics and correlations

Variables	**Mean**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. CSP	28.447	14.596	1.000							
2. WOCB	0.160	0.094	0.298***	1.000						
3. F100	0.213	0.409	0.381***	0.201***	1.000					
4. Firm size	9.380	1.210	0.449***	0.232***	0.648***	1.000				
5. ROA	7.829	7.963	0.042**	0.006**	0.067***	-0.150***	1.000			
6. Leverage	24.437	16.693	0.006	0.035**	-0.035**	0.078***	-0.229***	1.000		
7. R&D	4.786	16.142	-0.016	-0.015	0.008	-0.094***	-0.189***	-0.101***	1.000	
8. Board indep.	0.824	0.103	0.239***	0.222***	0.140***	0.160***	-0.053***	0.064***	0.010	1.000
VIF	-	-	1.34	1.10	1.86	1.96	1.20	1.09	1.10	1.07

The asterisks *** and ** indicate significance at the 1% and 5%, levels, respectively.

Table 3
Main results

	Pooled OLS	Fixed effects	System GMM	Control function		
				Second stage		First stage
				Exogenous	Endogenous	WOCB
	(1)	(2)	(3)	(4)	(5)	(6)
CSP_{t-1}	0.9144	0.5050***	0.8872***	0.8913***	0.8900***	---
	(0.0082)	(0.0171)	(0.0348)	(0.0111)	(0.0111)	
WOCB	2.3921**	2.1230	4.5067	2.3502**	43.1849*	---
	(1.1578)	(2.1180)	(3.0297)	(1.1701)	(25.1849)	
FSIZE	0.7220***	1.3510***	0.6424	1.3687***	0.0644	0.0312***
	(0.0995)	(0.4024)	(0.4660)	(0.4341)	(0.9351)	(0.0052)
ROA	0.0458***	0.0381**	0.0166	0.0477**	0.0471**	0.0000
	(0.0142)	(0.0176)	(0.0235)	(0.0194)	(0.0194)	(0.0003)
LEV	-0.0056	-0.0167	-0.0187	-0.0298*	-0.0466**	0.0004*
	(0.0066)	(0.0155)	(0.0253)	(0.0170)	(0.0200)	(0.0002)
R&D	0.0028	0.0050	-0.0018	0.0013	0.0090	-0.0002
	(0.0065)	(0.0109)	(0.0061)	(0.0120)	(0.0129)	(0.0002)
BINDEP	3.7707***	3.5913*	0.3482	2.7652	-2.4733	0.1286***
	(1.0791)	(1.9458)	(3.5713)	(2.1268)	(3.9484)	(0.0300)
F100	---	---	---	---	---	0.0141**
						(0.0057)
First-stage residual	---	---	---	---	-40.8762	---
					(25.9606)	
Year dummies	Yes	Yes	Yes	Yes	Yes	---
Within averages	---	---	---	Yes	Yes	Yes
Initial conditions	---	---	---	Yes	Yes	---
Constant	-4.7658***	---	---	-10.5664***	-5.1500	-0.0961***
	(1.4119)			(1.4017)	(3.7145)	(0.0248)
Rank test (*p*-value)	---	---	---	---	---	0.0130
Hansen test (*p*-value)	---	---	0.1043	---	---	---
AR(1) (*p*-value)	---	---	0.0000	---	---	---
AR(2) (*p*-value)	---	---	0.7876	---	---	---

Variables are defined in Table 1. This table reports empirical results from estimating Eq. [1], using (1) an OLS model, (2) an FE model, (3) a two-step system GMM, and (4) a CF approach. Variables are defined in Table 1. Robust standard errors are shown in parentheses. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix

In this appendix, we present our model in detail. The model we estimate can be written as:

$$y_{1it} = z'_{1it}\beta_1 + \beta_2 y_{2it} + \rho y_{1i,t-1} + c_{1i} + \eta_t + u_{1it},\ i = 1, \ldots, N \text{ and } t = 1, \ldots, T \quad \textbf{[A1]}$$

where y_{1it} denotes the performance index of firm i at time t, y_{2it} is the indicator of WOCB of firm i at time t, $\mathbf{z}_{1it}$ is a vector of control variables, c_{1i} is firm i FE, and u_{it} is the usual two-sided error term. In the application the following values hold:

- y_{it} = ROA
- w_{it} = WOCB
- z'_{it} = (firm size, ROA, leverage, R&D, board independence)

This model is often called the *structural* model with a control function approach (Wooldridge, 2015).

This model allows for two types of unobserved heterogeneity among firms: a time-constant unobserved heterogeneity, c_{i1t}, and time-varying unobservable, u_{it}. Thus, there are two kinds of potentially omitted variables. The time-constant heterogeneity, c_{i1t}, may be correlated with explanatory variables, that is, y_{2it} and $\mathbf{z}_{1it}$. Second, the time-varying omitted variables captured by the error term u_{it} are, by definition, uncorrelated with $\mathbf{z}_{1it}$—strict exogeneity—but may be correlated with y_{2it}. These two issues can be addressed simultaneously using the correlated random effect estimator proposed by Mundlak (1978) and the control function approach as summarized in Wooldridge (2015), as shown in the next section.

In addition to unobserved heterogeneity, an issue known as the initial condition problem can occur in dynamic modeling such as shown in model [A1] (Heckman, 1981). This problem originates from the potential correlation between the unobserved FE c_{1i} and the lagged value of the performance index $y_{1i,t-1}$, or, a fortiori, between c_{1i} and the initial value of the performance index $y_{1i,0}$. It has been shown that, if the initial correlation problem is ignored, uncorrected heterogeneity not only leads to an overstatement of the impact of the lagged value of the performance index $y_{1i,t-1}$, the state dependence effect, but also could lead to an understatement of the impacts of other explanatory variables, in particular $y_{2i,t}$ (Heckman, 1981). A correlated random effect estimator, as developed by Wooldridge (2005) and Skrondal and Rabe-Hesketh (2014), can be used to address the initial condition problem.

Now consider first the endogeneity issue for $y_{2i,t}$. Suppose we have a vector of instrumental variables we denote by $\mathbf{z}_{2it}$. These instrumental variables are, by definition, excluded from model [A1] and are strictly exogenous (conditional on c_{i1}). In the application,

$\mathbf{z}'_{2it} = F100$.

Using a control function approach, it is thus assumed that the endogenous explanatory variable y_{2it} can be expressed as a linear projection on strictly exogenous variables, or a reduced form model, such that:

$$y_{2it} = \mathbf{z}'_{1it}\,\delta_1 + \mathbf{z}'_{2it}\,\delta_2 + c_{2i} + u_{2it} \quad \textbf{[A2]}$$

where c_{2i} is firm i FE, and u_{2it} is the usual two-sided error term. Note then that the classical rank condition for identification in an IV estimation can now be written as $\delta_2 \neq 0$ and tested using a classical F-test.

Eq. [A2] can be estimated using a classical FE estimator, but this approach prevents the use of any time-invariant regressors in this equation. Another estimation strategy could then use the correlated random estimator proposed by Mundlak (1978). This estimator is based on the assumption that the FE c_{2i} can be expressed as:

$$c_{2i} = \bar{z}_i \, \lambda + a_{2i} \quad \textbf{[A3]}$$

where the j^{th} component of vector $\bar{z}_i$ is the within-firm average variable $\mathbf{z}'_{jit}$, or $\bar{z}_{ji} = T^{-1} \Sigma_{t=1}^{T} z_{jit}$, and a_{2i} is usual random noise. Then, plugging Eq. [A3] into Eq. [A2], this latter becomes:

$$y_{2it} = \mathbf{z}'_{it} \, \delta + \bar{z}_i \, \lambda + v_{2it} \quad \textbf{[A4]}$$

where $\mathbf{z}_{it} = (\mathbf{z}'_{1it}, \mathbf{z}'_{2it})'$ and $v_{2it} = a_{2i} + u_{2it}$. This equation can be estimated by pooled OLS as $E(a_{2i} + u_{2it} \mid \mathbf{z}_{it}) = 0$. Then note that (1) the correlated random estimator approach can be showed to be equivalent to the FE estimation, (2) the effects of time-invariant variables can be estimated using it, and (3) a simple test of correlation between c_{2i} and $\bar{z}_i$ can be performed testing $H_0 : \lambda = 0$ using a classical F-test.

Endogeneity of y_{2it} arises in Eq. [A1] if and only if u_{1it} in Eq. [A1] is correlated with u_{2it} in Eq. [A2]. We can summarize this by writing the linear projection of u_{1it} on u_{2it} as:

$$\begin{aligned} u_{1it} &= \theta \, u_{2it} + e_{1it} \\ &= \theta \, (v_{2it} - a_{2i}) + e_{1it} \end{aligned} \quad \textbf{[A5]}$$

where $\theta \equiv E(u_{2it} \, u_{1it})/E(u_{1it}^2)$ is the population regression coefficient. Note that, by construction, $E(u_{2it} \, e_{1it}) = 0$ and $E(z_{it} \, e_{1it})$ because both u_{1it} and u_{2it} are uncorrelated with z_{it}. Accordingly, $E\left(y_{2it} \, e_{1it}\right) = 0$.

Plugging Eq. [A5] into Eq. [A1], the latter becomes:

$$\begin{aligned} y_{1it} &= \rho \, y_{1i,t-1} + \beta_2 \, y_{2it} + \mathbf{z}'_{1it} \, \beta_1 + c_{1i} + \theta \, (v_{2it} - a_{2i}) + e_{1it}, \text{ or} \\ y_{1it} &= \rho \, y_{1i,t-1} + \beta_2 \, y_{2it} + \mathbf{z}'_{1it} \, \beta_1 + \theta \, v_{2it} + (c_{1i} - \theta \, a_{2i}) + e_{1it}, \text{ or} \\ y_{1it} &= \rho \, y_{1i,t-1} + \beta_2 \, y_{2it} + \mathbf{z}'_{1it} \, \beta_1 + \theta \, v_{2it} + c_{0i} + e_{1it} \end{aligned} \quad \textbf{[A6]}$$

where $c_{0i} = c_{1i} - \theta \, a_{2i}$. v_{2it} can be now viewed as an additional explanatory variable in Eq. [A1]. The introduction of this additional variable makes it possible to avoid the problem of endogeneity of y_{2it} when estimating β_2 in Eq. [A6].

But we are still faced with the problem of a possible correlation between the FE c_{0i} and explanatory variables, including the lagged value $y_{1i,t-1}$ (the initial condition problem). Wooldridge (2005) extends Mundlak's correlated random effect estimator by adding initial condition $y_{1i,0}$ to a within-firm average of variables $\mathbf{z}_{1it}$ in a regression model similar to Eq. [A3] to handle this last issue. In addition, Skrondal and Rabe-Hesketh (2014) suggest improving the Wooldridge (2005) approach by imposing initial values on all explanatory variables, that is, $\mathbf{z}_{1i0}$, to avoid potential estimation bias, especially for a panel with a limited number of survey rounds. Firm FE c_{0i} is thus expressed as:

$$c_{0i} = \alpha_{y0} \, y_{1i,0} + \mathbf{z}'_{1i0} \, \alpha_{z0} + \bar{\mathbf{z}}'_{1i} \, \alpha_z + a_{1i} \quad \textbf{[A7]}$$

Finally, plugging Eq. [A7] into Eq. [A6], we get the augmented model:

$$y_{1it} = \rho \, y_{1i,t-1} + \beta_2 \, y_{2it} + \mathbf{z}'_{1it} \, \beta_1 + \theta \, v_{2it} + \alpha_{y0} \, y_{1i,0} + \mathbf{z}'_{1i0} \, \alpha_{z0} + \bar{\mathbf{z}}'_{1i} \, \alpha_z + a_{1i} + e_{1it} \quad \textbf{[A8]}$$

where, now, $E\left(a_{1i} + e_{1it} \middle| y_{2it}\right) = 0$. This equation can be estimated using pooled OLS.

To sum up, estimation of the impact of WOCB is performed in two steps:

1. Estimation of the reduced form [A4] for y_{2it}, using pooled OLS, obtaining residuals $\hat{v}_{2it}$ for all (i, t) pairs
2. Estimation of the augmented regression model [A8] for y_{1it}, where we replace $v_{2it}, y_{1i,0}$, and $\boldsymbol{z}_{1i0}$ by estimated values $\hat{v}_{2it}$ and initial observations, respectively, using pooled OLS, testing endogeneity of y_{2it} that is now equivalent to testing $H_0 : \theta = 0$ using robust t-statistics

Because of the two-step procedure, the standard errors in the second step are known to be incorrect. Murphy and Topel (2002) propose a general method of calculating the correct asymptotic covariance matrix for the second-step estimators, but this method entails complicated calculations. Instead, we prefer to estimate the robust standard errors in the second step using a bootstrap technique, that is to say, by resampling the firms a large number of times. This number can be fixed following Davidson and MacKinnon (2000).