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Does board gender diversity influence firm profitability? A control function approach

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ABSTRACT

We investigate the relation between board gender diversity and firm profitability using the control function (CF) approach recently suggested by Wooldridge (2015). The CF method takes account of the problem of endogenous explanatory variables that have potential to bias the results. Using a sample of firms that made up the S&P 500 over the period 2004-2015, we find that the presence of women on corporate boards (measured either by the percentage of female directors on corporate boards or the Blau index of heterogeneity) has a positive and significant (at the 1% level) effect on firm profitability (measured by the return on assets). We compare our results to more traditional approaches (such as pooled OLS or the fixed-effects model). Through this study, we shed light on the effect of women on corporate boards on firm performance, as it is still a controversial issue (Post and Byron, 2015).

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1. Introduction

In recent years, board gender diversity (BGD) – or women on corporate boards (WOCB)[2] – has been at the center of policy and academic research (Terjesen, Sealy and Singh, 2009). Previously considered to be an ethical issue (i.e. that it is wrong for individuals to be excluded from the highest echelons of organization purely on the grounds of gender), WOCB is increasingly perceived as a value-driver for organizations. Robinson and Dechant (1997) have suggested a "business case" for BGD, arguing that it may improve board decision-making, which, in turn, may influence firm performance (FP).

The academic literature puts forward several arguments in support of BGD, including enhanced quality of decision-making (Milliken and Martins, 1996), a closer monitoring of boards' strategic decisions (Nielsen and Huse, 2010), and board behavior (Adams and Ferreira, 2009), which, in turn, induce better firm performance. However, these claims have not been confirmed empirically. Despite a relatively large body of literature examining the relationship between WOCB and firm performance, the empirical evidence is somewhat mixed (Post and Byron, 2015). Some studies have found that WOCB add value (e.g. Campbell and Mínguez-Vera, 2008, Liu, Wei and Xie, 2014). Conversely, other studies have documented that WOCB decrease firm performance (e.g. Adams and Ferreira, 2009, Ahern and Dittmar, 2012). Finally, some studies have found that WOCB have no effect on firm performance (e.g. Carter, D'Souza, Simkins and Simpson, 2010, Rose, 2007).

Many reasons could explain such a mixed set of findings, with potential candidates including the use of different samples, time windows, empirical specifications, and methodologies (Adams, Haan, Terjesen and Ees, 2015, Ferreira, 2015). We believe that such empirical inconsistency may be due to a failure to take endogeneity problems into account (Adams, 2016). Establishing a causal relationship between BGD and firm performance might be challenging, because board characteristics are not exogenous random variables. Board characteristics are endogenously chosen by firms to fulfill their operating and contracting environment (Adams, Hermalin and Weisbach, 2010, Sila, Gonzaleza and Hagendorff, 2016). Three sources of endogeneity may bias the effect of board structure and firm performance (Wintoki, Linck and Netter, 2012). First, omitted or unobserved firm characteristics (both fixed and time-varying) may simultaneously affect both the appointment of female directors and firm performance. A second problem is reverse causality: WOCB may affect firm performance, but it is also possible that financially healthy firms are more likely to appoint female directors. Finally, dynamic endogeneity may arise when current firm value and board structure are attributable to past firm performance. Accordingly, not fully addressing the endogeneity issue may induce erroneous inferences about a causal relationship between BGD and firm performance. We argue that the inconsistency in results mentioned by Post and Byron (2015) is due partly to this phenomenon. Furthermore, the mixed results indicate that more evidence is needed to increase the level of knowledge regarding the relationship between BGD and firm performance.

Various econometric approaches have been proposed and used to investigate the relationship between BGD and FP, some of which, such as the generalized method of moments (GMM), address the problem of endogeneity explicitly. The main contribution of this article is to re-examine this relationship using the control function (CF) suggested by Wooldridge (2015). Specifically, we combine a correlated random effects (CRE) approach (Chamberlain, 1984, Mundlak, 1978) with a CF approach (Wooldridge, 2015)[3] to address the problem explicitly of endogeneity in a panel data framework. The endogeneity issue due to the omission

[2] We use both expressions in this study.

[3] Recent applications of the CF approach can be found in Giles and Murtazashvili (2013) and López-Feldman and Chávez (2017), among others.

of time-invariant factors that are correlated to WOCB is usually addressed using fixed-effects (FE) modeling. However, the CRE approach has more benefits than the traditional FE estimator in panel data analysis. First, by including the vector of time-averaged explanatory variables, time-invariant unobserved heterogeneity can be controlled as with FE but without encountering the incidental parameter problem that affects FE model estimation. Second, it enables measuring the effect of time-invariant explanatory variables, which FE modeling does not allow (Wooldridge, 2010). Moreover, CRE can be easily combined with a CF approach, which addresses the potential endogeneity issue due to unobserved time-varying factors that are correlated with WOCB. The CF approach is inherently an instrumental variables (IV) method. Its implementation assumes the availability of variables that do not appear in the equation to be estimated, that is, excluded instrumental variables, and that explains the variation of the endogenous explanatory variable, here WOCB. The exogenous variation induced by excluded instrumental variables provides a separate variation in the residuals obtained from a reduced form, which serve as the control functions. By adding appropriate control functions, which are usually estimated in a first stage, the endogenous explanatory variable becomes appropriately exogenous in a second-stage equation. Accordingly, the CF approach enables testing the endogeneity of the explanatory variable by using a simple Hausman (1978) test. This test first can be corrected from having estimation errors coming from first-stage estimation of control functions using bootstrap techniques, and then can be easily made robust to heteroskedasticity and serial correlation in a panel data setting. In doing so, we make an econometric contribution by specifically taking into account the different facets of endogeneity through the CF approach (Wooldridge, 2015) that have not yet been used in the literature on WOCB.

Under this framework, the purpose of this article is to provide new evidence regarding the relationship between BGD and firm profitability by taking into careful consideration the issue of endogeneity through the CF method. Based on upper echelon theory (UET), we examine if WOCB positively influence firm profitability.

The remainder of the article is structured as follows. Section 2 presents the theoretical framework and the hypothesis developed. Section 3 outlines the research design (focusing on the CF method). The results and concluding remarks are offered in Sections 4 and 5, respectively.

2. Theoretical background

As Post and Byron (2015) point out, a large number of theories, such as agency theory (Fama and Jensen, 1983, Jensen and Meckling, 1976), resource dependence theory (Pfeffer and Salancik, 1978), social identity theory (Ashforth and Mael, 1989), and social categorization theory (Tajfel, 1981), have served as theoretical frameworks to examine the link between BGD and FP. Following Post and Byron (2015), we use UET (Hambrick, 2007, Hambrick and Mason, 1984) as our main theoretical framework in this study. Originally, UET focused on the top management team (TMT). However, the literature has applied this theory to boards of directors by considering the latter as "supra top management teams" (Finkelstein, Hambrick and Cannella Jr., 2009): 11). UET assumes that directors differ in terms of cognitive frames and that these cognitive differences significantly influence firm outcomes (Hambrick, 2007). However, because directors' cognitive frames are difficult to measure, the literature proxies cognitive frames through observable characteristics of directors, such as gender or age (see (Dezsö and Ross, 2012).

Hambrick (2007) defines directors' cognitive frames as their information-seeking and information-evaluation processes. He argues that directors' cognitive frames are linked to their own experiences, knowledge, and values and fundamentally shape how they seek and inter-

pret the information they receive. This also significantly influences decision-making processes, thus firm outcomes. Following Hillman, Cannella and Harris (2002) and Singh, Terjesen and Vinnicombe (2008), we argue that female and male directors differ significantly regarding their cognitive frames and that gender diversity in the boardroom is likely to influence FP (e.g. Carpenter, 2002)

First, the literature has found that female directors bring different cognitive frames to a board due to variations in their experiences and knowledge compared to their male counterparts. For instance, compared to male directors, females are more likely to possess a university degree and hold advanced degrees (e.g. Dang, Bender and Scotto, 2014, Singh et al., 2008). In terms of work experience, female directors are less likely to have been CEOs or COOs[4] and are more likely to have come from non-business backgrounds (e.g. Dang et al., 2014, Singh et al., 2008).

In another vein, Daily, Certo and Dalton (1999) have suggested that WOCB are likely to bring to boards new insights and different understandings of market segmentation. A market segmentation strategy involves sound knowledge of the various market segments, as well as the different groups of consumers, in order to propose an attractive marketing mix (e.g. Dickson and Ginter, 1987, Smith, 1956). Accordingly, Daily et al. (1999) argue that WOCB expand perspectives to meet local and global needs, especially for firms operating in markets with a high concentration of female buyers (e.g. the luxury or automotive sector).

Second, owing to these differences in cognitive frames, we argue that a greater representation of female directors is likely to influence the decision-making processes of a board (Post and Byron, 2015). Specifically, we contend that an increase in female representation on corporate boards significantly influences *how* decisions are made. Women's leadership styles are said to be more participative, democratic, and communal (Eagly, Johannesen-Schmidt and Van Engen, 2003) than those of men, who are more likely to be autocratic (Eagly and Johannesen-Schmidt, 2001). This is supported by Bart and McQueen (2013), who find that female directors make fair decisions when competing interests are at stake by virtue of their cooperative decision-making.

The literature has shown that diverse groups have the potential to provide critical and valuable information through bringing a greater range of perspectives to a board because of their experiences and differentiated knowledge (Hillman, Shropshire and Cannella, 2007). It is assumed that female directors have the capacity to exploit fully a firm's capability to generate profits from its assets and investments (Carter et al., 2010, Miller and del Carmen Triana, 2009). In this context, Galbreath (2016) also argues that WOCB enable firms to meet the expectations and demands of the various stakeholders, which, in turn, improves corporate social performance (Boulouta, 2013). Finally, by empowering a multitude of viewpoints and cultivating deliberativeness in decision-making, WOCB might improve a firm's decision-making processes and thus the quality of the results of that decision-making (Loyd, Wang, Phillips and Lount Jr, 2013, van Ginkel and van Knippenberg, 2008). Finally, in addition to these cognitive differences that female directors bring, they are more likely to be independent directors (e.g. Dang et al., 2014, Singh et al., 2008) and to bring a different resources from that of men.

Consequently, we hypothesize that BGD is likely to be positively related to FP. Accordingly, we assert the following:

Hypothesis: All else being equal, BGD is positively related to FP.

[4] CEO: chief executive officer and COO: chief operating officer.

3. Research design

3.1. Sample

The initial sample included all companies listed on the Standard & Poor's 500 (S&P 500) as of December 31, 2015. It covers the period from 2004 to 2015. This index represents a broad cross-section of the US equity market, including stock traded on the New York Stock Exchange (NYSE) and Nasdaq. The S&P 500 captures more than 80% of the total domestic US equity float-adjusted market capitalization. This index has already been used in previous studies (e.g. Anderson and Reeb, 2003, Carter et al., 2010). This study focused exclusively on large-sized companies because they are more likely to be under scrutiny from various stakeholders in regard to BGD (Hillman et al., 2007).[5]

Following standard practice, financial (SIC codes 6000-6999) and utility (SIC codes 4900-4999) firms were excluded due to their particular features (in terms of specific disclosure requirements and accounting regulations). Finally, observations with insufficient data were also excluded from the analysis. The final sample consisted of 369 firms and 3,332 firm-year observations.

Finally, all variables except the dummy variables are winsorized at the 1% and 99% levels to reduce the potentially spurious effects of outliers.

3.2. Variables definition

3.2.1. Dependent variable

Consistent with Wintoki et al. (2012), our main measure of performance is return on assets (ROA), calculated as operating income before depreciation divided by total assets (Adams and Ferreira, 2009, Wintoki et al., 2012). ROA is an indication of the ability of a firm to generate accounting-based revenues in excess of actual expenses from a given portfolio measured on a historical basis. As such, ROA represents an indication of the accounting income produced for the shareholders (Carter et al., 2010).

Many studies that examine the relationship between BGD and FP have also used Tobin's Q as a measure of performance (e.g. Adams and Ferreira, 2009). However, two reasons motivated us to choose ROA as our measure of performance. First, Wintoki et al. (2012) argue that the use of Tobin's Q as a measure of performance might be a proxy for growth opportunities. However, there are theoretical foundations suggesting that growth opportunities are a cause, rather than a consequence, of governance structures. Boone, Field, Karpoff and Raheja (2007) and Linck, Netter and Yang (2008), among others, provide empirical evidence to support this line of reasoning.

Second, in their meta-analysis of 100 studies examining the link between WOCB and FP, Post and Byron (2015) found that BGD is positively and significantly related to accounting returns (such as ROA). This suggests that firms with a greater proportion of WOCB have higher accounting returns. By contrast, these authors do not find any significant relationship between WOCB and market performance (such as Tobin's Q). Venkatraman and Grant (1986) question if Tobin's Q and ROA can be treated as equivalent, interchangeable measures of FP.

3.2.2. Independent variable

Following Adams and Ferreira (2009), BGD was measured through the percentage of WOCB calculated as the number of female directors divided by the total number of directors.

[5] Consistent with the existing literature (e.g. Adams and Ferreira, 2009, Carter et al., 2010), this study focuses on the US market because it is the largest market in the world and is more analyzed and commented on by the academic literature, politics, and the press around the world.

3.2.3. Control variables

Following prior studies, such as Bebchuk and Cohen (2005) or Adams and Ferreira (2009), we controlled for firm and board characteristics that may affect our measure of performance.

Specifically, we first included *Firm size* (approximated using the natural logarithm of total assets; (Hillman et al., 2007). Firm size is a key driver of firm value and FP. Large firms are associated with higher costs of monitoring, because they are more complex to lead. Consistent with the existing literature, we expected a negative relationship between firm size and firm financial performance (e.g. Adams and Ferreira, 2009, Isidro and Sobral, 2015). Second, we included *Leverage* (calculated as the ratio of total debt to total assets; (Campbell and Mínguez-Vera, 2008). According to Shleifer and Vishny (1997), leverage is an important governance mechanism that forces managers to generate enough cash flow in order to pay the interest and the principal. This will then mitigate agency conflicts resulting from cash flow. As a result, we expected a negative relationship between leverage and firm financial performance (e.g. Campbell and Mínguez-Vera, 2008, Isidro and Sobral, 2015). Third, we included *R&D Intensity* (measured as the R&D-to-sales ratio; (Honoré, Munari and de La Potterie, 2015). Higher research and development (R&D) investment is usually associated with superior performance (e.g. Chan, Martin and Kensinger, 1990, Eberhart, Maxwell and Siddique, 2004). Hence, we expected R&D intensity to be positively related to FP. Fourth, we controlled for *firm's growth* (defined as sales growth between *t* and *t*-1), because Green and Jame (2013) argue that a firm's operational growth is an important vector of FP. Consistent with Isidro and Sobral (2015), we expected a positive relationship between firm growth and FP. Finally, we included *Firm age* (measured as the natural logarithm of the number of years since the firm's inception; (Anderson and Reeb, 2003). Older firms are often associated with organizational rigidity and rent-seeking behavior by managers, which can cause FP to deteriorate. Conversely, age may bring knowledge and skills. Green and Jame (2013) show that FP declines with firm age. Therefore, we expected a negative relationship between firm age and FP.

In our specification, we also included a set of control variables related to the BoD's structure, namely, board size, board independence, and board leadership structure. van den Berghe and Levrau (2004) argued that these three board mechanisms are the most commonly used in the literature. The empirical literature examining the relationship between BGD and FP has generally used these three control variables (e.g., Adams and Ferreira, 2009, Dezsö and Ross, 2012), as well as in the CG literature (e.g., Bebchuk and Cohen, 2005, Wintoki, Linck, and Netter, 2012). As pointed out by Adams, Hermalin, and Weisbach (2010), these board variables enables controlling both for the quality of CG and their possible effects on FP.[6] First, we included *Board size* (measured as the logarithm of the number of directors on the board; (Wintoki et al., 2012). The arguments for a positive relationship between board size and FP stem from resource dependence theory, which posits that larger boards will have better information or greater knowledge due to the higher number of directors (e.g. Carter et al., 2010). However, proponents of agency theory posit a negative relationship (e.g. Yermack, 1996). Both theoretical and empirical evidence suggest that we should boar size in any specification, even if the direction of the relationship is not certain. Second, we considered *Board independence* (measured as the proportion of outside – non-executive – directors on the board; (Wintoki et al., 2012). The effect of board independence on FP remains an open question in the literature (e.g. Adams and Ferreira, 2009, Bhagat and Bolton, 2008). Following Adams

[6] Because the aim of this article is to compare our results from CF with the existing empirical literature, we did not add any further control governance variables (such as ownership structure). However, we are aware that there are potentially other control governance variables. However, it is unclear, based on the existing literature, if adding these variables would significantly alter the relationship between BGD and FP (Adams, Almeida, and Ferreira, 2009, Adams et al., 2010).

and Ferreira (2009) and Carter et al. (2010), we included board independence as a control variable although the direction of the relationship is uncertain. Finally, we added *CEO duality* (measured as a dummy variable that is equal to 1 if the CEO is also the chair, 0 otherwise; (Wintoki et al., 2012). Existing studies have found that CEO duality is likely to have an impact on FP. Consequently, CEO duality is a double-edged sword on FP (Finkelstein and D'aveni, 1994).

3.3. Methodology

3.3.1. Endogeneity issues in estimating the relationship between board gender diversity and FP

According to Adams et al. (2010), there is no convincing reason to believe that board structure is exogenous. Indeed, there are both theoretical arguments and empirical evidence that suggest board structure is actually endogenous (e.g. Hermalin and Weisbach, 1988, 1998, 2003). For instance, Hermalin and Weisbach (1998) argue that board structure reflects an equilibrium resulting from a bargaining process between the CEO and the board. The CEO's bargaining position stems from his or her ability (for which FP is a proxy). As such, board structure depends on past performance. Hermalin and Weisbach (2003) argue that board structure and FP are jointly endogenous. Furthermore, Fama and Jensen (1983) and Coles, Daniel and Naveen (2008), among others, argue that board structure is a function of the scope and complexity of the firm.

The prospect that BGD is a conscious choice made by a firm must be taken into account when estimating the relationship between BGD and FP (Adams and Ferreira, 2009). Consequently, in this study, we specifically consider this endogeneity problem, following Hambrick (2007), who highlighted that this issue is "essential for gaining a grasp of the causal mechanisms that lie behind empirical associations" (p. 338).

However, in order to examine the relationship between BGD and FP accurately, two alternative explanations must be considered: omitted/unobserved factors and reverse causality (Adams and Ferreira, 2009, Sila et al., 2016).

3.3.2. Omitted/unobserved factors

Omitted variable bias and unobserved heterogeneity are variables, other than those specified in the model, that can provide an alternative or additional explanation to phenomena under study (Gippel, Smith and Zhu, 2015). According to Adams et al. (2009) and Adams (2016), this is a major problem, especially when estimating the relationship between BGD and FP, because a firm's characteristics (both fixed and variable across time) may affect both the appointment of female directors and the governance choices made by an organization.

For instance, based on institutional theory (DiMaggio and Powell, 1983, Meyer and Rowan, 1977), the larger and more visible an organization is, the greater the pressure put on it to comply socially. Hillman et al. (2007) emphasize the fact that large listed companies are subject to much attention and are particularly exposed to the scrutiny of a variety of stakeholders (e.g. employees, customers, investors, and communities) to increase female representation at all levels of the organization, especially in the boardroom. We also know that large firms behave differently from small ones regarding gender diversity (Martín-Ugedo and Minguez-Vera, 2014). If we do not properly account for firm size, this factor could play a role in the observed correlation between BGD and corporate boards. Consequently, the eventual outcomes could suffer from omitted variable bias, making it difficult to determine the magnitude of the causal effect of gender diversity (Adams, 2016).

In the same vein, firms that are concerned about female representation on corporate boards may be more likely to appoint directors (the demand side) or may have a larger pool of female

candidates on which to draw for board positions (the supply side; see Gabaldon, Anca, Mateos de Cabo and Gimeno, 2015). On the demand side, socially responsible organizations may be more likely to be progressive and appoint WOCB, because female director appointments are a means of displaying their legitimacy to stakeholders (Carleton, Nelson and Weisbach, 1998, Hillman et al., 2007). Within this framework, BGD is a component of corporate social responsibility (CSR) and corporate social performance (CSP). Empirical studies have shown a positive association between BGD and CSR/CSP (e.g. Byron and Post, 2016). On the supply side, socially responsible organizations may appear to be very attractive in the eyes of female directors (Hillman et al., 2007, Turban and Greening, 1997). Indeed, social identity theory suggests that individuals seek to surround themselves with people who share similar perspectives and values, particularly as a basis for group membership (Dutton and Duncan, 1987, Tajfel and Turner, 1986). Adams and Funk (2012) find in their sample that female directors are more likely to possess what Eagly et al. (2003) labelled *communal traits*:[7] universalism and benevolence, among others.

Firm-specific unobserved variables, that is, unobserved variables that represent time-invariant properties of firms, such as national institutional systems (Grosvold and Brammer, 2011) or cultural effects towards BGD (Carrasco, Francoeur, Labelle, Laffarga and Ruiz-Barbadillo, 2015), may significantly affect the relationship between BGD and FP. Indeed, Grosvold and Brammer (2011) and Carrasco et al. (2015) argue that country-level institutions play a significant role in the female representation on corporate boards, and cultural traits significantly affect a firm's performance. However, these antecedents may be difficult to observe and measure so they are usually omitted from econometric specifications.

In this context, whatever the source of the omitted variable bias (which, moreover, can be cumulative), it is possible to observe a statistical relation between BGD and FP, even in the absence of a causal relationship between the two variables. In general, the literature deals with this issue by using panel data analysis and FE estimators, because these can take into account this bias under certain assumptions (Wooldridge, 2010). However, this treatment may not be sufficient because of a second explanation: reverse causality (Adams and Ferreira, 2009).

3.3.3. Reverse causality

Another problem associated with endogeneity is reverse causality (or simultaneity), which occurs when the dependent variable and the variable of interest are jointly determined (Gippel et al., 2015). There might be a source of endogeneity in the relationship between BGD and FP, because the match between corporate boards and female directors is likely to be a function of both firm and individual characteristics (Adams, 2016). Specifically, any correlation between corporate outcomes and BGD may be the result of both the effect of WOCB on outcomes and the effect of outcomes on BGD. In performance specifications, WOCB may affect FP, but it is also possible that financially successful firms may be more likely to appoint female directors (Adams and Ferreira, 2009). Not taking into account reverse causality in the specification might produce biased results, because the direction of causality could go both ways (Gippel et al., 2015). Beyond these two sources of endogeneity, Wintoki et al. (2012) categorized a third source of endogeneity: dynamic endogeneity.

3.3.4. Dynamic endogeneity

Generally, the term *dynamic endogeneity* refers to the type of endogeneity that arises when a firm's current actions are correlated to its control environment and future performance (Wintoki et al., 2012). In a general framework of the relation between governance and performance, endogeneity could arise when the current corporate governance mechanisms, con-

[7] In essence, communal traits encompass caring, sensitivity, honesty, understanding, compassion, and sympathy (Eagly et al., 2003).

trol characteristics, and FP are determined by the firm's past performance. For instance, if a firm suffers from poor performance, it is likely that this situation will prompt shareholders to replace board members who will issue more stringent governance rules. This is likely to affect the firm's current board structures, some control characteristics, and performance (Hermalin and Weisbach, 1998). Consequently, Wintoki et al. (2012) argue that corporate financial decisions are likely to be dynamic in nature. Raheja (2005) and Harris and Raviv (2008) hypothesize that past performance has a direct influence on a firm's innovation environment or potential profits. All these factors (individually and collectively) might affect the optimal board structure, including female representation on corporate boards. Consequently, Wintoki et al. (2012) refer to this relationship as dynamic endogeneity. They find that, in the US market, a dynamic relationship between current governance and past FP exists. Their results imply that, if the dynamic endogeneity problem is not carefully controlled, the relation between current board structure and past performance is likely to yield inconsistent results.

3.3.5. Identification strategy

Our main model is as follows:

$$(FP)_{it} = \rho\ (FP)_{it-1} + \beta\ (\text{BGD measure})_{it} + (\text{Control variables})'_{it}\ \Upsilon + \text{Year dummies} + (\text{Firm fixed effect})_i + \varepsilon_{it} \quad \textbf{[1]}$$

where i denotes firms in the sample, and t refers to time period. $(FP)_{it}$ is a measure of firm i performance at time t. As recommended by Wintoki et al. (2012), we express current FP as a linear function of past performance, choosing a lag equal to one. $(\text{BGD measure})_{it}$ is a measure of measure of firm i BGD at time t, either WOCB or Blau. $(\text{Control variables})_{it}$ is a vector of observable control variables influencing firm i performance at time t. The model includes year dummies and firm FE to capture unobservable time-varying unobserved factors and unobservable time-invariant firm heterogeneity. ρ, β and the vector Υ are parameters to be estimated given a panel sample of firm observations.

Modeling the present performance of a firm as a function of its past performance, while introducing a FE to capture the unobserved time-invariant firm heterogeneity, as assumed in Eq. [1], results in the 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 OLS to Eq. [1] can be shown to be inconsistent.

Existing studies (e.g. Adams and Ferreira, 2009, Liu et al., 2014) use the FE panel estimator to mitigate potential endogeneity of BGD arising from unobserved time-invariant firm heterogeneity and/or simultaneity. However, the FE estimator is not designed to deal with an initial condition problem. It can be also shown that, for a fixed number of time periods in the panel data set, the FE estimator raises an inconsistent estimation of the effect of past performance on present performance (Nickell, 1981). This inconsistency is not caused by anything we can assume for the FE, because these are eliminated by within transformation in estimation. The problem is that the within transformed lagged performance measure is now correlated with the within transformed error (Verbeek, 2012).

The two-step system GMM estimator, proposed by Blundell and Bond (1998), appears to be the most feasible solution for dealing with issues that come from a dynamic panel setting, such as Eq. [1]: (i) potential correlation between firm FE and some control variables, (ii) endogenous explanatory variable (here, BGD measure), and (iii) initial condition problem (Wintoki et al., 2012). Moreover, this technique overcomes the unavailability of appropriate external instruments for BGD measure as often encountered in the literature. Indeed, this technique enables employing the internal instruments available within the panel itself by eliciting all the moment conditions data must satisfy. Recent simulation studies document the good performance of a two-step system GMM when dealing with issues encountered estimat-

ing panel data models such as Eq. [1] (Flannery and Hankins, 2013, Zhou, Faff and Alpert, 2014). Nevertheless, this technique is not free of limits. As emphasized by Roodman (2009a), the number of internal instruments generated using system GMM increases as the number of time periods T increases and can be shown as a quadratic in T. Instrument proliferation then makes some asymptotic results about system GMM estimators and render related specification tests to be misleading. A large instrument number often leads to overfitting endogenous variables and weakening the Hansen *J*-test of the instruments' joint validity (Roodman, 2009a). Estimated variances of coefficients and the Hansen *J*-test can be too small, resulting in too much confidence in the validity of internal instruments. Roodman (2009a) proposes techniques for fighting against instrument proliferation. One of them is to combine, or to collapse, internal instruments through addition into smaller sets. This technique has the potential advantage of retaining most of the information conveyed by internal instruments and is equivalent to imposing the constraint in projecting regressors onto internal instruments that certain subsets have the same coefficient. Roodman (2009a) also provides simulation results showing the relevance of this technique.[8]

System GMM has been proposed as an alternative to instrumental variable methods when no external instrument variable is available. Identifying valid instruments is a difficult task in BGD analysis, because the majority of observable firm characteristics are already included in the performance equation. Reguera-Alvarado, de Fuentes and Laffarga (2017) propose using a measure related to firm visibility as an external instrument. Specifically, they propose to operationalize this visibility by using a firm's membership in the stock market index. Such information is available to firms belonging to our sample. We observe if a firm is listed or not in the S&P 100 index. Because this index encompasses the largest companies in US, we hypothesize that those firms are expected to have higher visibility, due to their higher exposure to investors, stakeholders, media, and so on, especially regarding BGD (Hillman et al., 2007).

The availability of external instruments enables us to define an alternative strategy to the usual approaches in BGD analysis, based on recent developments in CRE and CF approaches (Wooldridge, 2015). 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 FR 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 chosen BGD indicator.

All in all, the empirical version of Eq. [1] we estimate is given by:

$$\begin{aligned}(\mathrm{FP})_{it} = {} & \rho\,(\mathrm{FP})_{it-1} + \beta\,(\text{BGD measure})_{it} + \Upsilon_1\,(\mathrm{FSIZE})_{it} + \Upsilon_2\,(\mathrm{LEV})_{it} + \Upsilon_3\,(\mathrm{R\&D})_{it} \\ & + \Upsilon_4\,(\mathrm{GROWTH})_{it} + \Upsilon_5\,(\mathrm{FAGE})_{it} + \Upsilon_6\,(\mathrm{BINDEP})_{it} + \Upsilon_7\,(\mathrm{BSIZE})_{it} \\ & + \Upsilon_8\,(\mathrm{DUAL})_{it} + \text{Year dummies} + (\text{Firm fixed effect})_i + \varepsilon_{it}\end{aligned} \qquad \textbf{[2]}$$

3.4. Descriptive statistics and correlation analysis

Table 1 reports the descriptive statistics of all the variables. The mean ROA is 7.92%. However, there is a large variation in ROA within the sample firms, as the minimum is −17.22% and the maximum is 29.47%. Compared to Adams and Ferreira (2009) and Carter et al. (2010), among others, the firms in our sample enjoyed a better economic performance: the aforementioned studies finding mean (ROA) values of 3.19% and 3.90%, respectively. This is probably due to our time window being more recent (2004–2015), compared to 1996–2003 and 1998–2002, respectively.

[8] See also the technical recommendation in appendix B of Wintoki et al. (2012).

The mean (resp. median) percentage of WOCB is approximately 16% (resp. 17%), which is significantly higher than the 8.50% reported by Adams and Ferreira (2009). The more recent time period of our study may explain the difference. Approximately 85% of the firms in our sample have at least one female director. This proportion is much larger than the 61% reported by Adams and Ferreira (2009). Finally, the average number of WOCB is 1.76, whereas Carter et al. (2010) reported 1.30 for their sample. In a nutshell, female directors seem to have made significant inroads on governance bodies.

Relative to Carter et al. (2010), the firms in our sample are larger in terms of assets (9.37 vs. 8.35)[9] and managed by slightly smaller boards (10.72 vs. 9.38; Adams and Ferreira, 2009). Compared to Adams and Ferreira (2009), the firms in our sample are more independent (83% vs. 63%). Finally, relative to Carter et al. (2010), 58% (vs. 71%) of the firms in our sample have CEOs acting as chairs.

Ultimately, given these differences, the firms in our sample seem to have significant differences with existing studies. This observation has to be underlined.

[Place Table 1 here]

Table 2 reports the correlations among the variables. As a rule of thumb, a correlation of 0.70 or higher in absolute value may indicate a multicollinearity issue (Liu et al., 2014). In Table 2, the highest correlation of 0.49 appears between firm size and board size, which is well below the value of 0.70.

To make sure that multicollinearity is not a problem in Eq. [4], we calculated the variance inflation factors (VIFs) for all the variables (Wooldridge, 2014). The VIFs ranged from 1.02 to 2.31, well below the cut-off of 10 recommended by Wooldridge (2014). Consequently, we concluded that multicollinearity had little impact on our analyses.

[Place Table 2 here]

4. Results

4.1. Main results

Table 3 presents the estimates of Eq. [2] with the percentage of WOCB, our measure of BGD, through the use of alternative models: (i) a dynamic OLS model (column 1), (ii) a FE model (column 2), (iii) a two-step system GMM (column 3), and (iv) our proposed strategy combining CF and CRE (columns 5 and 6). To test our hypothesis, we only consider results that reach conventional significance levels of 1% and 5%.

A first striking result appears in Table 3: the coefficient associated with past performance is found to be positive and significantly different from zero (at 1% significance level), regardless of the method used. The expectation that pooled OLS estimator overestimates the true coefficient on the lagged firm performance, whereas the fixed effects estimator will underestimate it (Bond, 2002), is satisfied. Estimates of the lagged firm performance coefficient using system GMM and joint CRE and CF estimators belong in the range defined by the values estimated using pooled OLS or FE estimators.

This first result supports Wintoki et al.'s (2012) claim that performance is path-dependent, that is, past performance has a significant effect on current performance, and that this path dependence must be taken into account when measuring the causal effect of corporate board features such as WOCB. Nguyen, Locke and Reddy (2014), among others, find a similar result.

[9] Logarithmic values.

Consistent with existing literature (e.g. Rose, 2007), as shown in column 1 of Table 3, the percentage of WOCB is positively and significantly correlated to ROA at a 5% level of significance when using pooled OLS model. This finding is consistent with Campbell and Mínguez-Vera (2008) and Liu et al. (2014), among others. However, when time-invariant unobserved heterogeneity is taken into account through firm FE, the sign of the relationship turns out to be negative but significant only at the 10% level (column 2 of Table 3), suggesting that the relation between BGD and FP may be neutral, which is consistent, for example, with Carter et al. (2010).

Following Wintoki et al. (2012), we used the two-step system GMM estimator to examine the effect of WOCB on firm performance. Internal instruments were collapsed in order to deal with the issue of instrument proliferation (Roodman, 2009a, b). The results reported in column 3 of Table 3 shows that the percentage of WOCB is negatively and statistically significantly related to ROA, but only at the 10% level. Given our criteria of significance, we argue that the effect of WOCB on ROA seems to be neutral. This finding confirms Wintoki et al. (2012) claim that when using a dynamic system GMM the relationship between corporate governance and firm performance might be neutral. Additionally, our results are consistent with Adams and Ferreira (2009) in that when endogeneity is taken into account, the relationship between and FP is negative, as our figures show.

To examine the validity of the system GMM estimator statistically, we conducted a Hansen *J*-test.[10] Table 3 shows that the Hansen *J*-test yields a *p*-value of 0.015, clearly indicating rejection of the validity of the overidentifying restrictions involved in two-step system GMM estimation.[11] This result leads us to question the validity of the choice of internal instruments in the framework of system GMM, or the specification used in Eq. [2]. An alternative approach, therefore, appears necessary. This is made possible by the availability of an external instrument, namely *F100*.

Column 5 in Table 3 reports estimates when applying our proposed estimation strategy combining CF and CRE. Before going into detail about the coefficient estimates, we need to establish whether our instrument (*F100*) is significantly related to the percentage of WOCB. A valid instrument must meet two conditions (Baum, 2006): (1) not be correlated with the error term in the main performance equation, except through control variables included in the regression (instrument exogeneity), and (2) be correlated with the endogenous variable (instrument relevance). Results of the estimation of the auxiliary regression (see the Appendix) are shown in column 6 of Table 3. The percentage of WOCB clearly appears to be positively and significantly correlated (at 1% level) to *F100*. This instrument has a significant effect on the percentage of WOCB after controlling for other firm characteristics and taking into account the potential correlation between firm FE and these control variables and the initial condition problem. Moreover, we follow Andrews, Stock, and Sun (2019), who advised, as good practice, the use of Olea and Pflueger's (2013) *F*-statistics for detecting weak instruments in overidentified, non-homoskedastic settings with one endogenous explanatory variable. We compute the empirical counterpart of this *F*-statistic and report it in Table 3. The val-

[10] The assessment of instrument suitability in the case of system GMM is based on Hansen's overidentifying restrictions test.
It is well known that, due to internal instrument proliferation, this test is far too optimistic in the sense it rejects the null hypothesis in far too few cases. When the number of instruments is large, the overidentifying restrictions test may therefore fail
to indicate any misspecification or invalid instrumentation (Roodman, 2009a, b). For instance, this author gets *p*-values equal to 1 using simulations, even if the GMM system is invalid.

[11] It is noticeable that, without collapsing internal instruments, a two-step system GMM leads to Hansen *J*-test statistics with
an associated spurious *p*-value of 1.

ue obtained is 12.247, which is larger than the Staiger and Stock (1994) rule-of-thumb cutoff of 10. This value clearly indicates that the chosen instrument is relevant and cannot be considered as weak. Consequently, the chosen instrument is relevant.

As emphasized by Wooldridge (2014), because instrument exogeneity involves the covariance between the instrument and the unobserved error in the firm performance equation, we cannot generally hope to test this assumption. In the vast majority of cases, we must maintain the assumption of instrument exogeneity by appealing to economic behavior or introspection, as done by Reguera-Alvarado, de Fuentes, and Laffarga (2017). Nevertheless, instrument exogeneity also means that the instrument should have no association with FP after endogenous explanatory variables and omitted variables have been controlled for. Put differently, Reguera-Alvarado et al. (2017) noted that the chosen instruments must be uncorrelated with FP, except through variables that we control for. To check our chosen instrument exogeneity, we thus compute the correlation between *F100* and the residual of the regression of ROA on WOCB, lagged ROA, and the control variables. The estimated correlation is about −0.021 and is not significantly different from zero (whereas the correlation between ROA and *F100*, although small, is significantly different from zero). Even if we do not have here a formal test as to the exogeneity of the chosen instrument, such as the Hansen overidentification test,[12] this absence of a correlation seems to be in favor of exogeneity of *F100*. This result confirms the works of Reguera-Alvarado et al. (2017) that the visibility of a firm can be a good instrument for BGD.

Column 5 of Table 3 reports the augmented version of the Eq. [2] estimation where the possibility that the percentage of WOCB is endogenous is taken into account by the use of the estimated residual of the auxiliary regression as an additional explanatory variable. Our results clearly show that WOCB must be considered as endogenous because an estimated first-step residual appears to be significantly different from zero using a bootstrapped robust standard error. As such, the estimated coefficient of WOCB is positively and significantly different from zero (at the 1% significance level). Everything else being equal, a one standard deviation increase of WOCB would increase ROA by: 1.214 * 6.92% = 8.41%, an amount that is significant.

Now consider the control variables we included in Eq. [2]. By definition, these control variables are introduced because they might control directly for confounding factors. In other words, these variables are added to the regression model to control for potential unobserved time-variant factors that may cause the causal variable, here WOCB, to be endogenous. The statistical requirement for this to work is that the distribution error term in Eq. [2] should be conditionally independent of the causal variable when introducing the control variables (Wooldridge, 2014). These latter may not have any causal interpretation, meaning that the interpretation of their impact may be wrong. Nevertheless, it should be noticed here that, consistent with previous studies (e.g. Adams and Ferreira, 2009), firm size has a negative and significant effect (at the 5% level) on FP in models 1, 2, and 5. This result suggests that larger firms have more complex activities and are more difficult for investors to monitor. As expected, leverage is, in all models, negatively and significantly (at the 1% level) correlated to firm profitability, suggesting that leverage is not an efficient mechanism, in our sample firms, for reducing agency conflict in a firm. Our results are consistent with Isidro and Sobral (2015). Additionally, in all models, we find that firm growth is positively and significantly correlated to ROA (at the 1% level), which is consistent with Isidro and Sobral (2015). Finally, we notice that firm age is negatively and significantly correlated to ROA (at the 5% level), suggesting that FP fades with time (Green and Jame, 2013).

[12] This test cannot be implemented here because we have only just-identification, that is, one instrument for one endogenous explanatory variable.

Regarding board characteristics, we find that the coefficients for board size and board independence are not significantly different from zero in almost every model. This is consistent with Adams and Ferreira (2009). Furthermore, we find that CEO duality is negatively and significantly correlated to ROA (at the 5% level) in model 5. Our results are consistent with agency theory (Fama and Jensen, 1983, Jensen, 1993), which considers that CEO duality has a negative effect on FP.

[Place Table 3 here]

4.2. Robustness checks

Following Campbell and Mínguez-Vera (2008) and Triana, Miller and Trzebiatowski (2013), we use the Blau index as an alternative measure of BGD. The Blau (1977) index of heterogeneity is measured as $(1-\sum p_i^2)$, where p_i is the percentage of board members in each category *i* (in this case, male and female directors). Blau's index can range from 0 (i.e. all board members are male) to 0.50 (which occurs when there is an equal number of female and male directors). The Blau index of BGD ranges from 0.00 (i.e. no WOCB) to 0.50 (half of the board are female directors).

According to panel A in Table 4, the average (median) value of the Blau index is 0.25 (0.28), which is significantly higher than those reported by Campbell and Mínguez-Vera (2008) and Triana et al. (2013): 0.05 and 0.19, respectively.[13]

Table 4 shows results similar to those in Table 3 when the Blau index was our measure of BGD: first, FP is still path-dependent because the coefficient related to one-year lagged ROA is found to be positively and significantly correlated to ROA (at the 1% level), regardless of the model considered. Second, once again, the Blau index must be considered as endogenous because an estimated first-step residual appears to be significantly different from using a bootstrapped robust standard error. As such, the estimated coefficient of the Blau index is positively and significantly different from zero (at the 1% significance level). Specifically, everything else being equal, a one standard deviation increase in the Blau index would increase ROA by 0.91 * 6.92% = 6.29%, an amount that is significant.

Regarding control variables, we find the same results as those presented in Tables 3.[14] The findings in Tables 3 and 4 support those of Campbell and Mínguez-Vera (2008) that the percentage of WOCB and the Blau index can be use as alternative measure of BGD. However, our results run counter to those of Solakoglu and Demir (2016), who argue that results may be affected by the measures of BGD used. It might be specific to their sample, because our findings indicate the opposite. However, this requires further investigation.

[Place Table 4 here]

Although Wintoki et al. (2012) thought that the use of Tobin's Q as a measure of performance might be problematic, we estimate Eq. [2] using Tobin's Q for robustness and comparability reasons similar to the existing empirical literature (e.g. Adams and Ferreira, 2009, Liu et al., 2014). Table 5 presents an excerpt of the results, which are qualitatively unchanged. In line with the base case analysis, in all models, we find that the coefficient on one-year lagged Tobin's Q is positive and significant (at the 1% level) compared to a current Tobin's Q, what-

[13] As with WOCB, we checked the two conditions that *F100* must meet as a potential instrument for the Blau index. Olea and Pflueger's (2013) *F*-statistics, whose value is 13.435, clearly shows the relevance of *F100*. Moreover, the estimated correlation between *F100* and the residual regression of ROA on lagged ROA, the Blau index, and other control variables is −0.022 and is not significantly different from zero. This is in favor of *F100*'s exogeneity.

[14] To avoid making the text more cumbersome, we will not discuss in detail those results.

ever the considered model. This suggests that past financial performance has a significant effect on current performance, as emphasized by Wintoki et al. (2012). Furthermore, in models 17 and 23, we find that our measure of BGD (either the percentage of WOCB or the Blau index) is positively and significantly correlated to Tobin's Q at the 1% level of significance. Thus, a one standard deviation increase in BGD would increase Tobin's Q by 14.31% and 10.96%, respectively. Finally, unreported, we find similar results for control variables.[15]

[Place Table 5 here]

5. Concluding remarks

5.1. Conclusions

Claims that BGD improves FP are abundant in the business press and in academic literature (Terjesen et al., 2009). However, there is no consensus in the literature regarding the effect of WOCB on FP, because the results are mixed (Post and Byron, 2015). This study seeks to shed light on this topic. Consistent with Wintoki et al. (2012) and Adams et al. (2009), we argue that not properly taking into account the problem of endogeneity that arises because of differences in unobservable characteristics across firms, reverse causality and dynamic endogeneity may induce erroneous inferences regarding the relationship between BGD and FP. The contrasting results mentioned by Post and Byron (2015) are probably explained by this observation. Accordingly, we pay careful attention to endogeneity issues that could mitigate the finding by using the CF method developed by Wooldridge (2015), instead of system GMM, which is classically used in the literature.

As emphasized by Roodman (2009b), the appeal of system GMM is based on the hope that this econometric technique would solve tough estimation issues in panel data modelling – fixed effects, endogeneity for regressors, and dynamic panel bias – in cases when good external instruments are lacking. Indeed, a large set of internal instruments can be built using all identifying moment conditions. But this is also the weaknesses in system GMM, namely, instrument proliferation. Specifically, instrument proliferation creates some asymptotic results for system GMM estimators and makes related specification tests appear misleading. A large instrument number often leads to overfitting endogenous variables and weakening the Hansen *J*-test of the instruments' joint validity (Andersen and Sørensen, 1996, Bowsher, 2002, Roodman, 2009b). Estimated variances of coefficients and the Hansen *J*-test can be too small, resulting in overfitting lagged dependent variables and too much confidence in the validity of internal instruments. Given that, one recommendation when dealing with the instrument proliferation issue is cautiousness when choosing internal instruments. Roodman (2009b) suggests restricting the number of lagged levels used in the instrument matrix, collapsing the instrument matrix, or combining the two. In the end, as Roodman (2009b) very rightly emphasizes, the system GMM might works but "under arguably special circumstances" (p. 156). Although attractive for addressing endogeneity issues, the system GMM approach might have serious limitations.

In this article, thanks to the availability of external instruments, we propose the CF method for addressing the endogeneity issue. Wooldridge (2010) defines CF as a proxy variable that renders an endogenous explanatory variable exogenous (when conditioned) in a regression. In essence, the CF approach is close to an IV approach.[16] One of the CF's attractions is the sim-

[15] Results are available on request from the authors.

[16] By definition, the CF approach is an instrumental variable approach and has been developed in econometric literature at the same time as a conventional IV estimation method or classical 2SLS. The CF approach puts more structure in the reduced form of the endogenous explanatory variables than classical 2SLS. In the very simple setting of a linear regression model with endogenous explanatory variables estimated using cross-

ple re-specification of the model through the introduction of new regressors to control for endogenous explanatory variables, as well as the computational tractability this specification yields (Wooldridge, 2010, 2015). CF provides a useful alternative to a system GMM approach. The CF approach might be easier to implement and is available in situations of instrument proliferation, provided some effort is made to find external instruments.

Overall, we find that BGD is positively and significantly (at the 1% level) correlated to FP, whereas system GMM shows that the relationship is not significant at the 5% level (or below). The economic effect is higher when BGD is considered to be exogenous. Our study tempers the assertion of Adams and Ferreira (2009) and Ferreira (2015) that when the endogenous characteristics of women's representation on corporate boards are taken into account, the relationship is necessarily negative. Our findings do not support this assumption. We argue that idiosyncratic characteristics of firms are likely to have a significant influence on the relationship between BGD and FP. Indeed, our results may be influenced by the critical mass of WOCB (Joecks, Pull and Vetter, 2013, Konrad, Kramer and Erkut, 2008). Critical mass theory (Kanter, 1977) suggests that the interactions within a group depend fundamentally on the size of the group. When a sub-group size reaches a certain threshold, or critical mass, the influence of this sub-group increases significantly. As shown in Table 2, the mean percentage of WOCB is about 16% (vs. 8.50% for Adams and Ferreira, 2009), with 21% of firms in the sample having at least three women on their corporate board. Joecks et al. (2013) argue that critical mass is a key component in assessing the relationship between BGD and FP. Consequently, different firms' idiosyncrasies may alter the link.

Consistent with Wintoki et al. (2012), we also find that past performance has a significant effect on the relationship between BGD and FP, confirming the claim of these authors regarding dynamic endogeneity. Our findings confirm the results of Farrell and Hersch (2005), who find a positive relationship between ROA and the likelihood of appointing a higher proportion of female directors to boards. Our study confirms some previous studies on the positive link between BGD and FP (e.g. Liu et al., 2014, Reguera-Alvarado et al., 2017).

Consequently, this article offers new insights regarding the relationship between BGD and FP (ROA and Tobin's Q) resulting from new US data and an alternative econometric approach (the CF method).

5.2. Implications

Our results offer some managerial insights and policy implications. First, we support, to some extent, the business case for BGD, since we find a positive and significant relationship between BGD and firm profitability. Second, our findings suggest that firms should have a more efficient view regarding having WOCB, as we show that a greater proportion of WOCB creates value of, more or less, 3% on ROA. This increase in firm economic performance is often accompanied by greater visibility and commitments to CSR, which in turn affects CSP (Boulouta, 2013). Third, this research has strong implications for both governments and lawmakers (market regulators), as well as shareholders and fund managers, in terms of enhancing public decision-making towards BGD and portfolio management.

5.3. Limitations

sectional data, the two approaches produce similar estimated values. In this setting, the main advantage of CF when compared to classical 2SLS is that the test of the null hypothesis that an explanatory variable suspected to be endogenous is exogenous reduces in the simple heteroskedastic-robust test of significance of the parameter associated with a first-stage residual in an augmented regression model. The traditional form of the Hausman test that directly compares OLS and 2SLS is substantially harder to make robust to heteroskedasticity. This advantage becomes all the more interesting when considering more complex models.

Our study is not without limitations. First, we analyze the impact of BGD on firm profitability in the US context (English-origin countries; see La Porta, Lopez-de-Silanes, Shleifer and Vishny, 1998). Grosvold and Brammer (2011) argue that institutional, cultural and political systems are important when analyzing the relationship between BGD and FP. Hence, further cross-country studies are necessary to confirm (or dispute) our findings, as they might be driven by national specificities. Second, our study focuses on the largest US listed companies in the S&P 500 index. Further studies are needed on small- and medium-sized firms, entrepreneurial and private equity firms, and public sector firms and non-profit organizations, since they are significantly different (e.g. in terms of capital structure or ownership). The differences may significantly affect the relationship between BGD and FP.

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Table 1

Descriptive statistics (N = 3,446)

Variables	Mean	SD	Median	Min.	Max.
ROA	7.916	6.925	7.582	−17.218	29.436
WOCB	16.005	9.336	16.667	0.000	41.667
Firm size[1]	25,427.86	41,777.04	10,416.43	1,121.605	253,753
Leverage (%)	24.367	16.223	22.823	0.000	73.811
R&D (%)	4.176	6.807	0.709	0.000	32.343
Firm growth (%)	7.707	18.018	6.236	−44.966	80.293
Firm age[1]	62.785	44.697	51.000	2.000	177.000
Board independence (%)	82.586	9.798	85.714	50.000	93.333
Board size[1]	10.728	2.042	11.000	6.000	16.000
Duality	0.581	0.493	1.000	0.000	1.000
S&P 100	0.205	0.403	0.000	0.000	1.000

Variables are defined in sub-section 3.2.

Table 2

Correlation matrix

		1	**2**	**3**	**4**	**5**	**6**
1	ROA	1.000					
2	WOCB	−0.002	1.000				
3	Firm size	−0.181***	0.211***	1.000			
4	Leverage	−0.256***	0.052***	0.082***	1.000		
5	R&D	0.054***	−0.008	−0.073***	−0.206***	1.000	
6	Firm growth	0.247***	−0.128***	−0.106***	−0.137***	0.088***	1.000
7	Firm age	0.027	0.236***	0.138***	0.127***	−0.128***	−0.180***
8	Board indep.	−0.070***	0.202***	0.162***	0.086***	0.055***	−0.125***
9	Board size	−0.117***	0.227***	0.491***	0.132***	−0.114***	−0.122***
10	Duality	−0.006***	0.098***	0.126***	0.064***	−0.162***	−0.027
		7	**8**	**9**	**10**	**11**	**12**
7	Firm age	1.000					
8	Board indep.	0.139***	1.000				
9	Board size	0.206***	0.108***	1.000			
10	Duality	0.193***	0.206***	0.050***	1.000		

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
VIF	1.22	1.20	1.13	1.17	2.31	1.09	1.10	1.02	1.14	1.10	1.40	1.10	1.92

Variables are defined in sub-section 3.2. *** indicates significance at the 1% level.

Table 3

Effect of BGD (WOCB) on firm performance

	Pooled OLS	Fixed Effects	System GMM	Control Function		
				Second stage		First stage
				Exogenous	Endogenous	WOCB
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged ROA	0.5080***	0.1380***	0.2027***	0.4397***	0.4192***	---
	(0.0165)	(0.0204)	(0.0451)	(0.0176)	(0.0179)	
WOCB (%)	0.0296**	−0.0416*	−0.0806*	0.0389***	1.2138***	---
	(0.0131)	(0.0235)	(0.0425)	(0.0130)	(0.2080)	
Firm size	−0.5426***	−0.9153**	0.0006	0.1259	−2.9795***	2.5490***
	(0.1143)	(0.4583)	(0.6011)	(0.5349)	(0.7839)	(0.6255)
Leverage	−0.0892***	−0.2103***	−0.1914***	−0.1998***	−0.2647***	0.0519**
	(0.0082)	(0.0173)	(0.0440)	(0.0191)	(0.0222)	(0.0261)
R&D	−0.0538***	−0.0590***	−0.0741***	−0.0136	0.0108	−0.0222
	(0.0073)	(0.0112)	(0.0232)	(0.0114)	(0.0121)	(0.0174)
Firm growth	0.0379***	0.0431***	0.0384***	0.0606***	0.0599***	0.0003
	(0.0038)	(0.0039)	(0.0088)	(0.0046)	(0.0046)	(0.0059)
Firm age	0.4074***	2.2215**	0.6197*	2.2137*	−3.6483**	4.8950***
	(0.1334)	(0.9450)	(0.3437)	(1.3362)	(1.6840)	(1.3193)
Board Indep.	0.0012	0.0227	0.1277***	0.0346	−0.1176	0.1325***
	(0.0125)	(0.0222)	(0.448)	(0.0251)	(0.0367)	(0.0337)
Board size	0.2729	−1.6588	−2.0717	−1.4218	−1.3084	−0.1174
	(0.6858)	(1.1714)	(2.005)	(1.2744)	(1.2666)	(1.8267)
Duality	0.0605	0.2880	−0.0456	0.0567	−0.6777**	0.4924
	(0.2469)	(0.4025)	(0.6562)	(0.2756)	(0.3031)	(0.3536)
F100	---	---	---	---	---	1.8658***
						(0.5545)
First-stage residual	---	---	---	---	−1.1796***	---
					(0.2084)	
Year dummies	Yes	Yes	Yes	Yes	Yes	---
Within averages	---	---	---	Yes	Yes	Yes
Initial conditions	---	---	---	Yes	Yes	---
Constant	9.1345***	---	---	6.7408***	34.5320***	−19.451***
	(1.9110)			(2.0077)	(5.2996)	(2.9332)
Olea and Pflueger's (2013) F-statistics	---	---	---	---	---	12.247
Hansen test (*p*-value)	---	---	0.0152	---	---	---
AR(1) (*p*-value)	---	---	0.0002	---	---	---
AR(2) (*p*-value)	---	---	0.6620	---	---	---

Note: This table reports empirical results from estimating Eq. [13]. Specifically, column 1 reports the results obtained from the OLS method with clustering at the firm level. Column 2 presents the results obtained from the fixed-effects (within-groups estimator) method. Finally, columns 3 to 5 present the results from the CF approach. Variables are defined in sub-section 3.2. Regressions in column 3 include time averages of the explanatory variables. Columns 4 and 5 include bootstrapped robust standard errors with 399 replications. Furthermore, regressions include time averages of the first-stage residuals. Robust standard errors are shown in parenthesis. The asterisks ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

Table 4

Effect of BGD (Blau index) on firm performance

Panel A: Descriptive statistics

Variable	Mean	SD	Median	Min.	Max.
Blau	0.252	0.125	0.278	0.000	0.486

Panel B: Estimation

	Pooled OLS	**Fixed Effects**	**System GMM**	**Control Function**		
				Second stage		**First stage**
				Exogenous	**Endogenous**	**Blau**
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Lagged ROA	0.5079***	0.1369***	0.2044***	0.4392	0.4189***	---
	(0.0165)	(0.0204)	(0.0473)	(0.0176)	(0.0179)	
Blau (×100)	0.0251**	−0.0413**	−0.0761**	0.0341	0.9083***	---
	(0.0102)	(0.0178)	(0.0306)	(0.0102)	(0.1588)	
Firm size	−0.5438***	−0.8990**	0.0156	0.1194	−3.1527***	3.5358***
	(0.1142)	(0.4582)	(0.5873)	(0.5347)	(0.7865)	(0.8027)
Leverage	−0.0889***	−0.2108***	−0.1870***	−0.1999	−0.2655***	0.0690**
	(0.0082)	(0.0173)	(0.0441)	(0.0191)	(0.0223)	(0.0335)
R&D	−0.0540***	−0.0594***	−0.0739**	−0.0135	0.0104	−0.0291
	(0.0073)	(0.0112)	(0.0341)	(0.0114)	(0.0121)	(0.0223)
Firm growth	0.0379***	0.0430***	0.0379***	0.0607	0.0600***	0.0003
	(0.0038)	(0.0039)	(0.0100)	(0.0046)	(0.0046)	(0.0076)
Firm age	0.4004***	2.2196**	0.6406*	2.1812	−3.8418**	6.6141***
	(0.1336)	(0.9444)	(0.3484)	(1.3358)	(1.7033)	(1.6932)
Board in-dep.	0.0005	0.0234	0.1248***	0.0346	−0.1105***	0.1662***
	(0.0125)	(0.0222)	(0.0448)	(0.0251)	(0.0358)	(0.0433)
Board size	0.1881	−1.5880	−1.8984	−1.4887	−3.2085**	1.8966
	(0.6896)	(1.1707)	(1.9863)	(1.2737)	(1.3020)	(2.3443)
Duality	−0.0571	0.2875	−0.0646	0.0642	−0.4559	0.4077
	(0.2467)	(0.4020)	(0.6600)	(0.2755)	(0.2889)	(0.4538)
F100	---	---	---	---	---	2.4429***
						(0.7117)
First-stage residual	---	---	---	---	−0.8978***	---
					(0.1591)	
Year dummies	Yes	Yes	Yes	Yes	Yes	---
Within averages	---	---	---	Yes	Yes	Yes
Initial conditions	---	---	---	Yes	Yes	---
Constant	9.2850***	---	---	6.9604***	36.9103***	−27.992***
	(1.9168)			(2.0125)	(5.6717)	(3.7643)
Olea and Pflueger's (2013) F-statistics	---	---	---	---	---	13.435
Hansen test (*p*-value)	---	---	0.0146	---	---	---
AR(1) (*p*-value)	---	---	0.0002	---	---	---
AR(2) (*p*-value)	---	---	0.6701	---	---	---

Note: see Table 3 for explanation.

Table 5

Effect of BGD on firm performance (Tobin's Q)

Panel A: WOCB

	Pooled OLS	Fixed Effects	System GMM	Control Function		
				Second stage		First stage
				Exogenous	Endogenous	WOCB
	(13)	(14)	(15)	(16)	(17)	(18)
Lagged Tobin's Q	0.8115***	0.4390***	0.7120***	0.8785***	0.8636***	---
	(0.0100)	(0.0151)	(0.0865)	(0.0114)	(0.0117)	
WOCB	0.0037***	−0.0028	0.0019	0.0022	0.1120***	---
	(0.0014)	(0.023)	(0.0036)	(0.0013)	(0.0221)	
First-stage residual	---	---	---	---	−0.1101***	---
					(0.0222)	
Olea and Pflueger's (2013) F-statistics	---	---	---	---	---	12.247
Hansen test (*p*-value)	---	---	0.0057	---	---	---
AR(1) (*p*-value)	---	---	0.0002	---	---	---
AR(2) (*p*-value)	---	---	0.2705	---	---	---

Panel B: Blau index

	Pooled OLS	Fixed Effects	System GMM	Control Function		
				Second stage		First stage
				Exogenous	Endogenous	Blau
	(19)	(20)	(21)	(22)	(23)	(24)
Lagged Tobin's Q	0.8107***	0.4391***	0.7127***	0.8779***	0.8630***	---
	(0.0099)	(0.0151)	(0.0877)	(0.0114)	(0.0117)	
Blau (×100)	0.0035***	−0.0019	0.0020	0.0019*	0.0858***	---
	(0.0011)	(0.0017)	(0.0028)	(0.0011)	(0.0169)	
Olea and Pflueger's (2013) F-statistics	---	---	---	---	---	13.435
Hansen test (*p*-value)	---	---	0.0042	---	---	---
AR(1) (*p*-value)	---	---	0.0002	---	---	---
AR(2) (*p*-value)	---	---	0.2711	---	---	---

Note: see Table 3 for explanation.

Appendix

In this appendix, we go into the chosen methodology into more detail. The model we estimate can be written as:

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

where y_{1it} denotes the performance index of firm i at time t, y_{2it} is the indicator of BGD 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,

- $y_{it} = ROA$
- $w_{it} = WOCB \text{ or } Blau$, and
- $z_{1it}^{'} = \begin{pmatrix} \text{firm size, leverage, R \& D, growth, firm age, board independence, board size} \\ \text{and duality} \end{pmatrix}$.

This model is often called the *structural* model in the 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 unobservables, u_{it}. Thus, there are two kinds of potential 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 using simultaneously 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 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:

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

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 IV estimation can now be written as $\delta_2 \neq 0$ and tested using a classical F-test.

Equation [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:

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

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

$$y_{2it} = \boldsymbol{z}'_{it} \, \delta + \bar{z}_i \, \lambda + v_{2it} \qquad \text{[A4]}$$

where $\boldsymbol{z}_{it} = (\boldsymbol{z}'_{1it}, \boldsymbol{z}'_{2it})$' and $v_{2it} = a_{2i} + u_{2it}$. This equation can be estimated by pooled OLS as $E(a_{2i} + u_{2it} \mid \boldsymbol{z}_{it}) = 0$. Then note that (i) the correlated random estimator approach can be showed to be equivalent to FE estimation, (ii) the effects of time-invariant variables can be estimated using it, and (iii) 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:

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

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, $E(y_{2it} \, e_{1it}) = 0$.

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

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

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 $\boldsymbol{z}_{1it}$ in a regression model similar to Eq. [A3] to handle this last issue. In addition, Skrondal and Rabe-Hesketh (2014) suggest improving Wooldridge (2005) approach by imposing initial values on all explanatory variables, that is, $\boldsymbol{z}_{1i0}$, to avoid potential estimation bias, especially for a panel with a limited number of survey rounds. Firm FE c_{0i} is thus expressed as:

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

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

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

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

To sum up, estimation of the impact of women's participation on corporate boards 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 $\widehat{v}_{2it}$ and initial observations, respectively, using pooled OLS, testing endogeneity of y_{2it} that is now equivalent to testing $H_0 : \theta = 0$ using a 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).