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The effect of board gender diversity on corporate social performance: An instrumental variable quantile regression approach

Maria Giuseppina Bruna^{a,1}, Rey Đặng^b, Aymen Ammari^c, L'Hocine Houanti^d

^a *IPAG Business School, France; Chair, "Towards an Inclusive Company"*

^b *ISTEC Paris, France*

^c *EM Strasbourg Business School, France*

^d *EM Normandie Business School, France*

ABSTRACT

Investigating a sample of firms from the S&P 500 Index (between 2004 and 2015), the paper addresses the relationship between the representation of Women on Corporate Boards (WOCB) and the Corporate Social Performance (CSP). It adopts the *instrumental variable quantile regression panel data (IV-QRPD) model*, suggested by Powell (2016), to solve endogeneity and heterogeneity issues. The article shows a strong "threshold effect": the impact of board feminization on CSP is nonlinear and changes along the quantiles of the performance distribution. Highlighting a contextual and multilevel phenomenon, the paper contributes to the CG literature offering main achievements on board's dynamics and inclusiveness.

Keywords

Board of directors

Quantile regression

Women on corporate boards (WOCB)

Corporate Social Performance (CSP)

JEL codes

C5

C21

G34

¹ Corresponding author.

Email addresses: maria-giuseppina.bruna@ipag.fr (M. G. Bruna), r.dang@istec.fr (R. Đặng), ammariaymen@yahoo.com (A. Aymen), houantil_hocine@yahoo.fr (L. Houanti)

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ABSTRACT

Investigating a sample of firms from the S&P 500 Index (between 2004 and 2015), the paper addresses the relationship between the representation of Women on Corporate Boards (WOCB) and the Corporate Social Performance (CSP). It adopts the *instrumental variable quantile regression panel data (IV-QRPD) model*, suggested by Powell (2016), to solve endogeneity and heterogeneity issues. The article shows a strong “threshold effect”: the impact of board feminization on CSP is nonlinear and changes along the quantiles of the performance distribution. Highlighting a contextual and multilevel phenomenon, the paper contributes to the CG literature offering main achievements on board’s dynamics and inclusiveness.

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1. Introduction

A key-topic in management research, the Corporate Social Performance (CSP) broadly encompasses all the organizational policies (ranging from teleological goals to designed programs, from phenomenological processes to operational practices...) related to firm's societal relationships and embraces their observable outcomes (Wood, 1991, p. 693; Bruna and Nicolò, 2020).

To what extent do the Women on Corporate Boards (WOCB) affect a company's CSR (Corporate Social Responsibility) (McWilliams and Siegel, 2001)? That is a relevant issue for decision-makers (governments, private and nonprofit organizations (Soares et al., 2011) and for the academia (Byron and Post, 2016), as well.

While the literature has been mainly focused on financial performance (Post and Byron, 2015), few studies have investigated the link between WOCB and CSP (Rao and Tilt, 2016). In addition, these works have yielded mixed results, documenting alternatively either a positive (e.g., Francoeur et al., 2019, Wasiuzzaman and Wan Mohammad, 2020), a negative (e.g., Husted and de Sousa-Filho, 2019, Zahid et al., 2020) or a null relationship (e.g., Hussain et al., 2018, Manita et al., 2018). Accordingly, the WOCB-CSP link remains ambivalent and academically undetermined.

Even though these mixed results can be attributable to the countries' specificities (governance systems, cultural backgrounds, institutional/legal frameworks etc.) and the heterogeneity in the investigation time interval as well as in the adopted methods (Adams et al., 2015), endogeneity issues offer a major explanation of the ambiguity in empirical achievements (Boulouta, 2013, Francoeur et al., 2019). The literature on corporate governance (CG) has showed that endogeneity is engendered by two sources (Wintoki et al., 2012): omitted firm-characteristics and reverse causality (simultaneity). Additionally, the relationship between CG and firm performance (FP) is dynamic in nature: past FP influences current FP, producing what Wintoki et al. (2012) call a "dynamic endogeneity". Accordingly, following Adams (2016), we argue that most of the empirical literature is plagued by endogeneity issues, hence, the mixed results on the WOCB-CSP relationship.

The empirical literature inconclusiveness may be, partially, engendered by methodological dissensus between the OLS (ordinary least squares) or the fixed-effect (FE) estimator. These approaches focus on the central tendency of a distribution where, in facts, the impact of explanatory variables may be differentiated following the levels of the dependent variable. Additionally, heavy-tailed distributions (extreme values increasing or decreasing the mean) are likely to skew the distribution. Consequently, following Li (2015), we argue that classical methods are not able to offer a suitable approach to establish causal relationships between WOCB and CSP.

Providing both a methodological and an empirical contribution to the existing literature, this paper reexamines the relationship between WOCB and CSP adopting a Quantile Regression (QR) method. This innovative approach enables to point out the effect of WOCB on CSP considering different firm-performance levels. That way, the article criticizes the conventional assumption on a constant and linear WOCB average effect (Conyon and He, 2017). The QR method has been used frequently in the economic literature (Chernozhukov and Hansen, 2008, Koenker, 2004). Nevertheless, in the CSR field, few studies have effectively employed this approach. This paper fills that gap, enlightening the WOCB-CSP debate adopting an instrumental variable quantile regression panel data (IV-QRPD) model, as developed by Powell (2016). As introduced by Chernozhukov and Hansen (2004, 2005, 2008), this approach can alleviate the endogeneity issues as well as the perturbing effects of the sample heterogeneity.

Technically, we adopt regression models with fixed effects to control for changing individuals and for industrial-sector characteristics, which may influence the implementation of strategies, investments, techniques and activities to deal with CSR issues.

Effectively, the fixed-effects models control for otherwise unmeasured year-specific (period) and firm-specific effects on the dependent variable (e.g., Hausman and Taylor, 1981, Mundlak, 1978). Any effects of these variables are removed - i.e., controlled - by subtracting the firm mean from each observation. The unique effect of the stable, but unmeasured, characteristics of each individual is the "fixed effect" from which the model takes its name (Kilbourne et al., 1994).

2. Methods

Our initial sample includes firms listed at the S&P 500 Index between 2004 and 2015. This index encompasses the 500 largest companies and covers approximately 80% of available market capitalization. It has already been used in previous studies (e.g., Boulouta, 2013, Manita et al., 2018). We exclude financial and regulated utilities firms as well as establishments providing either insufficient or incomplete data. Thus, the final sample consists of 369 firms and 3,236 firm-year observations.

The CSP has been approximated through the Bloomberg's ESG (environmental, social, and governance) disclosure score (e.g., Buchanan et al., 2018, Jain et al., 2016). The latter covers the three canonical dimensions of CSR: (1) Environment (e.g., water use or energy consumption), (2) Social (e.g., employees or human rights policy), and (3) Corporate Governance (CG). The Bloomberg's score is based on Global Reporting Initiative's framework (GRI, Global reporting Initiative, 2011), which is the most employed standard for voluntary ESG disclosure (e.g., Milne and Gray, 2013). Data are compiled crossing and mixing several sources of information (e.g., annual reports, CSR or integrated reports). Each indicator is weighted considering its importance and relevance and the industrial sector is taken into account (e.g., Jain et al., 2016). This score varies from 0.10 (the minimum score corresponding to an extremely poor ESG disclosure) to 100 (the maximum score). Consequently, the Bloomberg's score reflects both a firm's CSR policy and its performance in this area (Buchanan et al., 2018, Nollet et al., 2016).¹

Following Reguera-Alvarado et al. (2017), we use the firm's visibility as an instrumental variable, that is, belonging to the S&P 100 Index. This index encompasses the 100 major blue-chip companies, representing approximately 63% of the S&P 500 and a total of 51% of the US market capitalization². Accordingly, due to their visibility, these companies are probably subject to more scrutiny from stakeholders. Consequently, they can be more sensitive to ethics and CSR topics (Hillman et al., 2007). More precisely, we adopt a dummy variable that equals 1 if a firm belongs, in a given year, to the S&P 100 Index, and 0 otherwise.

The percentage of WOCB is the number of female directors divided over the total number of directors (Francoeur et al., 2019).

For an increased readability, Table 1 provides the readers with an overview of our control variables and their definitions as commonly shared in the literature (e.g., Boulouta, 2013, Francoeur et al., 2019).

[Place Table 1 here]

We adopt the following equation:

$$CSP_{it} = \beta_0 + \beta_1 CSP_{t-1} + \beta_2 WOCB_{it} + \sum_{k=1} \beta_k X_{k,it} + \varepsilon_{it} \quad [1]$$

where i and t denote firms in the sample and time period, respectively; X is a vector of covariates; and ε_{it} is the error term.

¹ Fundamentally, CSP is a measure of corporate societal performance, i.e. a proxy of the quality of dialogue between stakeholders/ecosystem and the firm. ESG reporting (such as Bloomberg's ESG disclosure score) is a tool to disclose societal information and to communicate with stakeholders.

² As of January 2017; see the Standard & Poor's website.

Following Adams (2016), Eq. [1] is affected by the endogeneity issue, arising from two main sources: (1) omitted/unobserved factors and (2) reverse causality.

1. Omitted/unobserved characteristics (both fixed and time-varying) may simultaneously affect the representation of both WOCB and CSP.
2. The corporate outcomes–board diversity relationship can represent either the effect of board diversity on outcomes or vice versa.

Additionally, the CG literature (e.g., Harris and Raviv, 2006, Raheja, 2005) claims that the CG-FP relationship is dynamic in nature, that is, the corporation’s contemporaneous performance and the CG characteristics are influenced by the past performance. Accordingly, there is another potential source of endogeneity in the CG-performance relationship, namely, “dynamic endogeneity” (Wintoki et al., 2012). Not accounting for endogeneity may yield biased and inconsistent results (Roberts and Whited, 2013).

QR enables a comprehensive picture between a dependent variable Y and an independent variable X at different points of a conditional distribution (Koenker and Bassett, 1978, Koenker and Hallock, 2001). Additionally, QR does not require strict assumptions regarding normality, homoskedasticity and the absence of outliers (Johnston and DiNardo, 1997).

In mean regression, the panel data allow for the inclusion of FEs to capture within-group variations. Many QR methods for panel data use the same assumptions. However, the additive FEs alter the underlying model. Here, we use the QR estimator for panel data (QRPD) with nonadditive FEs as suggested by Powell (2016).

The main advantage of this method relative to the existing quantile estimators with additive fixed effects FEs (α_i) is that it estimates the distribution of Y_{it} given D_{it} instead of $Y_{it} - \alpha_i$ given D_{it} . Powell’s (2016) approach provides with point estimates that can be understood in a similar way to those originated from cross-sectional regressions. It is also consistent with those derived from studies with a small T . Formally, we get the following relationship:

$$Y_{it} = D'_{it}\beta_j(U^*_{it}) \quad [2]$$

where Y_{it} is the firm’s CSP, β_j is the variable of interest (WOCB), and U^*_{it} is the error term encompassing several either fixed or time-dependent disturbance terms. The model is linear in parameters, and $D'_{it}\beta(\tau)$ strictly increases in τ . Generally, for the τ^{th} quantile of Y_{it} , QR relies on the following conditional restriction:

$$P(Y_{it} \leq D'_{it}\beta(\tau)/D_{it}) = \tau \quad [3]$$

Eq. [3] shows that the probability the outcome variable can be smaller than the quantile function is the same for all D_{it} and equal to τ . The Powell’s (2016) QRPD estimator assumes this probability to vary by individual and even within-individuals as long as the variation is orthogonal to the instruments. Consequently, RPD relies upon a conditional restriction and an unconditional restriction, letting $D_i = (D_{i1}, \dots, D_{iT})$.

$$\begin{aligned} P(Y_{it} \leq D'_{it}\beta(\tau)/D_i) &= P(Y_{is} \leq D'_{is}\beta(\tau)), \\ P(Y_{it} \leq D'_{it}\beta(\tau)/D_i) &= \tau \end{aligned} \quad [4]$$

Powell (2016) develops the estimator in an instrumental variable context given instruments $Z_i = (Z_{i1}, \dots, Z_{iT})$. His estimation uses a generalized method of moments. Sample moments are defined as:

$$\hat{g}(b) = \frac{1}{N} \sum_{i=1}^N g_i(b) \text{ with } g_i(b) = \frac{1}{T} \left\{ \sum_{t=1}^T (Z_{it} - \bar{Z}_i) [Y_{it} \leq D'_{it}b] \right\}, \quad [5]$$

where $\bar{Z}_i = \frac{1}{T} \sum_{t=1}^T Z_{it}$.

Using Eq. [4], the parameter set is defined as:

$$B = \{b/\tau - \frac{1}{N} \sum_{t=1}^N \mathbb{1}(r_{it} \leq D'_{it} b \leq \tau)\} \text{ for all } t. \quad [6]$$

Then, the parameter of interest is estimated as follows:

$$\hat{\beta}(\tau) = \underset{b \in \beta}{\operatorname{argmin}} \hat{g}_1(b) \hat{A} \hat{g}(b) \quad [7]$$

for some weighting matrix \hat{A} . We used the Markov chain Monte Carlo (MCMC) optimization method.

3. Empirical results

Table 2 reports the descriptive statistics. The mean (median) CSP is 28.45 (23.97) versus 17.00 for Jain et al. (2016), suggesting an improvement of CSR practices over the years. Additionally, the mean (median) percentage of WOCB is approximately 16% (17%), consistent with Boulouta (2013) and Francoeur et al. (2019).

Generally, data are normally distributed if the value of skewness (coefficient of asymmetry) is 0 and the kurtosis is lower than 3 (Mukherjee et al., 1998). Table 2 shows that none of our variables is close to 0, suggesting that they are not symmetrically distributed. Furthermore, the value of kurtosis is greater than 3 for all variables (except for CSP), suggesting the presence of extreme values. Moreover, in many cases, the mean is significantly different from the median, implying that the distribution of our data is not normal. Finally, following Razali and Wah (2011), we used the Shapiro-Wilk (S-W) test for univariate normality and Doornik-Hansen and Henze-Zirkle tests for multivariate normality.

As shown in the last column of the Table 2, the assumption on the normal distribution of the variable has to be rejected. The Doornik-Hansen ($\chi^2(2) = 3.95e+05$ and $p < 0.10$) and Henze-Zirkle tests ($\chi^2(2) = 34.32$ and $p < 0.10$) reject the null hypothesis of multivariate normality. Therefore, our variables do not perfectly fulfill the normality and no-outlier assumptions.

[Place Table 2 here]

For comparison purposes, Table 3 reports the results from OLS, FE, and GMM (generalized method of moments) methods because they have been previously used in the literature.

In all models, the coefficient of CSP with a lagged value is positive and significant (at the 1% level), suggesting that past CSP has an impact on current CSP. Consistent with the CG literature (e.g., Đăng et al., 2020, Wintoki et al., 2012), our finding implies that past CSP should be considered as an important element when reviewing the dynamic nature of the CG-CSP relationship (Nadeem et al., 2017).

Model 1 shows that WOCB are positively and significantly correlated (at the 1% level) to CSP. This is consistent with Hafsi and Turgut (2013) and Wasiuzzaman and Wan Mohammad (2020). When the unobserved firm FEs are considered, the coefficient for WOCB is not significantly different from zero (at the threshold of 10%) (Table 3). That 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). The coefficient for WOCB is not significantly different from zero (at the 10% level).³ This finding is consistent with Boulouta (2013) but contrasts with Francoeur et al. (2019).

Our mixed findings, summarized in Table 3, are consistent with the literature. Accordingly, following Conyon and He (2017), we reject the conventional assumption that the average ef-

³ Both Hansen-*J* and Wald chi-square tests suggest that the system GMM model seems well specified.

fect of WOCB is constant and linear across the CSP distribution. While the Quantile Regression method (QR) provides a contrasting picture of the reality, the empirical findings show that WOCB have a negative and significant effect (at the 1% level) on CSP at the 10th, 25th and median percentiles.

This suggests that WOCB produce a negative effect on CSP for low-performing firms. For these companies, the CSP level is relatively low, i.e. $CSP = 13.22, 15.19, \text{ and } 23.97$ for the 10th, 25th, and median percentiles, respectively⁴.

Conversely, at the 75th percentile, the effect of WOCB is positive and significant (at the 5% level), that is, for firms performing well in terms of CSP ($CSP_{\theta=0.75} \geq 40.08$). At the median, the relationship is neutral. The effect of WOCB on CSP appears as heterogeneous. Specifically, WOCB engender a positive vs negative effect on CSP for high- vs low-performing firms.

[Place Table 3 here]

4. Conclusion

Empirically grounded, this article has addressed the endogeneity issues that endanger the methodological robustness of a large number of existing studies investigating the influence of WOCB on CSP. The article, while successfully accounting for the ambiguity and ambivalence in the literature findings (Byron and Post, 2016), underlines the key-impact of the sample heterogeneity as well as of the simultaneity, reverse causality and dynamic endogeneity factors. To face these challenges, the paper, following Wintoki et al. (2012), has adopted a dynamic approach and employed the IV-QRPD method, as developed by Powell (2016).

Even if an increasing CSP mean and median suggest a global improvement of CSR programs and practices over time (within the investigated sample, sketching a pro-diversity evolution within companies, markets and society), the IV-QRPD method reveals that the feminization of the boards produces mixed results on CSP. Typically, it engenders either a positive versus a negative effect on CSP for high - versus low - CSR-performing firms. More specifically, our research shows a negative effect of board feminization at the 10th, 25th and 50th percentiles for low-CSR-performing firms and a positive effect at the 75th percentile for high-CSR-performing firms.

After controlling for endogeneity issues, the effect of WOCB on CSP appears highly heterogeneous and contextually volatile. Convergent with Conyon and He (2017), our findings reveal a “threshold effect”: the impact of board feminization on a firm’s CSP changes along quantiles of the performance distribution.

Congruent with Bruna et al. (2019), the article explains that companies showing a low-CSR firm performance are more likely to appoint female directors as tokens, inducing a passive (defensive) alignment to institutional constraints and a mimetic isomorphism, instead of encouraging the adoption of distinctive (and competitive) pro-diversity strategies. Prevalent within firms showing a low-CSR maturity (in terms of consciousness, strategy embeddedness and transversal operationalization), the tokenism relegates women on boards to dominated positions. This phenomenon frequently engenders attitudes such as “*loyalty by gratefulness*’ (*perception of being a ‘survivor of inequality’ [implying ...] trustworthiness and conformity to the board’s norms and majoritarian opinions*); *loyalty by fear of exclusion*’ (*fidelity [as...] an attitude to prevent sanction [...], despite the actor’s deep convictions*); and *‘pre-exit positioning*’ (*process of marginalization and stigmatization, [reducing a...] critical WOCB to silence—a deficit of ‘voice’*)” (Bruna & al., 2019, p. 922). Accordingly, within low-CSR-performing companies (that represent a large segment of the sample), female directors are frequently pressed to renounce to their *effective power* inside the board. Condemned to an *appearance of power* and a *veil of prestige*, these women are frequently constrained to aban-

⁴ Note that the estimated magnitude is close to zero.

don (or limit) their critical and contributive “voices” to prevent stigmatization and social marginalization as well as to brake an anticipated risk of exclusion.

When “silent” female directors are appointed, open discussions, which encourage criticism, reflexivity, creativity and continuous learning, are rarefied, penalizing *de facto* the effectiveness of CSR policies.

Conversely, when firms socially perform (at the 75th percentile), the effect of WOCB is positive and significant (at the 5% level). The cognitive diversity induced by the feminization of the boards feeds fecund effects on the CG and nourishes the CSR consciousness, strategic commitment and efficiency.

Relying upon this major outcome, the present paper contributes to the CG literature because it underlines a main achievement on board’s dynamics: the inclusiveness of corporate bodies (that impacts the effectiveness of women-administrators’ contribution to stakeholders’ dialogue) depends on the CSR maturity of the company.

From the methodological viewpoint, it enriches the existing literature on the topic through the demonstration of the relevance of the instrumental variable as a highly effective control levier for endogeneity and sample heterogeneity issues in a QR framework.

Moreover, it investigates a multilevel (micro and meso) psycho-socio-organizational phenomenon as the ambiguous effect of WOCB on CSP, considering the moderating impact of CSR maturity. That way, it promotes a deeper understanding of board gender diversity dynamics.

In fine, our findings presented in the paper call for a higher sensitivity in future research to contextual factors and encourage innovative designs embracing segmented firm-performance approaches to decode WOCB issues and to enlighten the corporate governance black-box.

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Table 1
Definition of control variables

Variable	Definition
Firm size	The natural logarithm of total assets
Firm performance	Income before depreciation divided by total assets (Return on assets = <i>ROA</i>)
Leverage	The ratio of total debt to total assets
R&D	R&D (research and development) divided by sales (<i>R&D</i>)
Crisis	A dummy variable that is equal to 1 if a considered year is during the financial crisis of 2008–2009, and 0 otherwise (<i>CRISIS</i>)

The source of the data is Bloomberg.

Table 2
Summary statistics (N = 3,236)

Variables	Mean	SD	Median	Min.	Max.	Skewness	Kurtosis	S-W test
CSP	28.45	14.60	23.97	6.20	76.76	0.76	2.59	13.326***
WOCB	0.16	0.09	0.17	0.00	0.55	0.37	3.25	7.982***
Firm size	9.38	1.21	9.26	5.97	13.59	0.42	3.02	7.996***
ROA	7.83	7.96	7.58	-61.82	46.84	-1.38	15.50	14.364***
Leverage	24.44	16.69	22.64	0.00	110.60	0.89	4.40	10.946***
R&D	4.79	0.67	16.14	0.00	540.07	21.10	598.03	18.630***
Crisis	0.21	0.40	0.00	0.00	1.00	1.46	3.12	3.255***

S-W: Shapiro-Wilk test with Z-statistics. *** indicates significance at the 1% level.

Table 3 WOCB and CSP

Variables	Pooled	FEs	System	Instrumental variable quantile regression panel data				
	OLS		GMM	(IV-QRPD)				
Model (Quantiles)	1	2	3	4 (Q10)	5 (Q25)	6 (Q50)	7 (Q75)	8 (Q90)
CSP _{<i>t-1</i>}	0.905*** (0.012)	0.508*** (0.026)	0.853*** (0.0399)	0.877*** (0.001)	0.975*** (0.000)	1.000*** (0.000)	0.918*** (0.001)	0.690*** (0.083)
WOCB	3.658*** (1.240)	2.272 (2.485)	1.209 (4.901)	-0.031*** (0.008)	-0.001*** (0.000)	-0.007*** (0.001)	0.005 (0.005)	0.291** (0.143)
Firm size	0.778*** (0.108)	1.311*** (0.442)	1.015 (0.640)	0.014*** (0.000)	0.001*** (0.000)	0.006*** (0.000)	0.019*** (0.001)	0.023*** (0.007)
ROA	0.043*** (0.014)	0.033 (0.020)	0.074 (0.080)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.002*** (0.000)	0.000 (0.002)
Leverage	-0.005 (0.006)	-0.013 (0.016)	-0.014 (0.032)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)	-0.002** (0.001)
R&D	0.000 (0.004)	0.005 (0.003)	0.011 (0.019)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	-0.000* (0.000)	-0.001*** (0.000)
Crisis	-0.084 (0.992)	4.536** (2.176)	1.309 (15.737)	0.012*** (0.001)	0.001** (0.000)	0.007*** (0.000)	0.020*** (0.006)	0.081*** (0.002)
Constant	-3.762*** (1.362)	-2.281 (4.575)	-5.373 (13.941)	0.691*** (0.062)	0.851*** (0.027)	0.919*** (0.013)	1.004*** (0.022)	1.215*** (0.071)
FE effects	No	Yes	Yes					
Year dummies	Yes	Yes	Yes					
<i>R</i> -squared	0.867	0.476						
<i>F</i> statistic	684.13***	64.49***						
Wald chi-squared statistic			2573.83***					
Number of instruments			80					
Number of clusters	363	363	363					
AR2 (<i>p</i> -value)			0.733					
Hansen- <i>J</i> test of over-identification (<i>p</i> -value)			0.320					

Column 2 reports the results obtained from the OLS method with clustering at the firm level. Column 3 presents the results obtained from a fixed-effects (within-group estimator) method. Estimations gained from a two-step system GMM approach are reported in column 4. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. *t*-Statistics of OLS and FE estimators are reported in parentheses and are based on robust standard errors corrected for potential heteroskedasticity and time-series autocorrelation within each firm. *z*-Statistics of the system GMM model are reported in parentheses and based on Windmeijer-corrected standard errors (Windmeijer, 2005). For IVQR, *p*-values are in brackets. Year dummies and industry dummies are unreported.