The Dynamic Causality between Corporate Social Responsibility and Corporate Political Activity: A Panel Vector Autoregression Approach

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ABSTRACT

The objective of this study is to assess the dynamic causality between corporate social responsibility (CSR) and corporate political activity (CPA). This research uses panel vector autoregression (VAR) model within the framework of generalized method of moments (GMM) with consideration to the time invariant characteristics of each organisation. Based on a sample of 100 World's Most Admired Companies (WMAC) listed in Fortune between 2007 and 2016, this study provides empirical evidences that the CPA negatively affects the CSR, while enhanced CSR does not warrant an enhanced CPA. The findings of this study contradict the notion propounded by the hypothesis of virtuous circle which states that there is a positive relationship and mutual reinforcement between CSR and CPA.

JEL Classification: C33, D72**,** G30

Keywords: Corporate social responsibility (CSR); corporate political activity (CPA); panel vector autoregression (VAR); generalized method of moments (GMM); Granger causality

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INTRODUCTION

Many questions surround the potential relationship between a firm's corporate social responsibility (CSR) and its corporate political activity (CPA). The 'political CSR' literature links CSR and political theory (e.g., Matten and Crane, 2005; Scherer and Palazzo, 2011) by arguing that CSR is 'political' in a broad sense, because it focuses on a firm's assumption of governmental roles and responsibilities in a global context in which weak governance may prevail. Yet, many firms also operate 'politically' in a more traditional sense, interacting with and influencing governmental decision-makers, i.e. corporate political activity (CPA). So far, little attention has been given to study the dynamic causality between corporate social responsibility (CSR) and corporate political activity (CPA) (Hond et al., 2014). The CSR predominantly focuses on the social and environmental responsibilities of organisations (Doh et al., 2012; Hillenbrand et al., 2013) towards the community. Meanwhile, in the context of CPA, the organisations adapt the governmental policies in ways that are favourable to them (Getz, 1997; Hillman et al., 2004) with strategies that are directed at appointed officials and politicians (Hillman and Hitt, 1999), such as the contributions of political action committee (PAC), lobbying, and political directorships (Doh et al., 2012).

Linking CSR and CPA, the hypothesis of virtuous cycle highlights the propensity of organisations that are more assertive with the government towards the ethical codes and the propensity of organisations that demonstrate cooperation with the government towards committing the philanthropic and resource contributions (Luo, 2001). Meanwhile, studies on how and whether CSR and CPA are aligned by the organisations are limited (Beloe et al., 2007). Typically, the existing studies assess CSR and CPA independently (Anastasiadis, 2014) with the exception for few studies that associate both CSR and CPA on the basis that CSR and politics are interconnected, involving the sense of governmental responsibilities (Scherer and Palazzo, 2007; Scherer and Palazzo, 2011; Anastasiadis, 2014). In view of the above, this study aims to assess the dynamic causality between CSR and CPA.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

CSR supports CPA

The acquired resources through the CSR efforts of the organisations support their political involvements, which lower their dependency on financial donations following the reduced political costs (Hond et al., 2014). Moreover, the diverse and solid connections with the community as well as the non-governmental organisations through CSR strengthen the political efficacy—as compared to the organisations without CSR—with the organisations' significant influence and issue positions (Hond et al., 2014; Rehbein, 2015; Lin et al., 2015; Rehbein and Schuler, 2013; Werner, 2015). In particular, the organisations make use of the information to communicate their issue positions in reaching out to the politicians (Wang and Qian, 2011). Additionally, extensive CSR activities enhance the status and visibility of organisations, which provide polity connections in securing their access to the political and legislative decision-making. Therefore, organisations with high CSR reputation are presented with higher political prospects (Schuler and Rehbein, 2005; Wang and Qian, 2011), which draw the interest of politicians and eventually assist the organisations' political initiatives (Hond et al., 2014). Based on the above arguments, it is hypothesized as:

H1: CSR positively correlates with CPA.

CPA supports CSR

As posited by Post et al. (1983), the CPA supports the scheme and implementation of outward engagement initiatives under the CSR. In fact, the political efforts made by the organisations also potentially enhance the economic sustainability of CSR (Hond et al., 2014). Additionally, significant knowledge on how to address the existing social and environmental issues through these political connections effectively assist the CSR investments made by the organisations (Hillman and Hitt, 1999; Hond et al., 2014; Peterson and Pfitzer, 2009). For instance, the established standards for inventive products and processes through these political connections lower the associated business and regulatory risks, which give way to steady, emerging markets. Besides, the

organisations may also propose their CSR policies and the expected results to these authoritative figures in prompting them to support these initiatives (Caulkin and Collins, 2003; Bendell and Kearins, 2005). Following their approval, these authoritative figures endorse these CSR initiatives, which render the credibility and legitimacy of the organisations in their CSR commitment. These credibility and legitimacy are also enhanced through the solid connections between these organisations and the governmental agencies. As reaffirmed by Peterson and Pfitzer (2009), the solid connections with these governmental agencies are more likely to increase the effectiveness of addressing societal issues successfully in the CSR commitment of these organisations. With the political support, the organisations may obtain and expand the resources for their CSR initiatives as well. Thus, this study postulates that the knowledge and endorsement from these political influences provide enhanced credibility and the necessary opportunities for the organisations to prioritize the development as well as the economic sustainability of CSR (Love and Kraatz, 2009). Hence, it is proposed as:

H2: CPA positively correlates with CSR.

PANEL VECTOR AUTOREGRESSION MODEL

The effects of endogenous and exogenous variables over one another pose complexities for the study to estimate the causality between CSR and CPA, particularly on the effect of one variable over another as well as the effects of multiple variables. Addressing that, the panel vector autoregression (VAR) model was applied for the estimation in a generalized method of moments (GMM) framework using Stata 14, which was previously introduced by Abrigo and Love (2016)[1]. In fact, the panel VAR model is highly relevant to the concurrent condition model. The orthogonal impulse response function (hereinafter IRF) has been applied in this study. As a rule, one variable's reaction (e.g. CSR) may generate a shock in another variable (e.g. an accurate assessment, estimation, and evaluation of CPA can be obtained by keeping the basic model's every single other variable consistent and by disregarding their progressions (shock)). This study focuses on the autoregressive panel VAR structure shown in Equation (1) without the loss of generality, disregarding the exogenous variables. Supposedly, the vector of k-endogenous variables for firm i at time t is $Y_{it} = [CSR_{it}, CPA_{it}]$' forms the underlying structure of the panel VAR model. Equation (1) presents the reduced-form dynamic relationship of the endogenous variables:

The profitability is considered as the most exogenous whereas the diversification is perceived as the most endogenous in the case of the first-order (Campa and Kedia, 2002; Villalonga, 2004). Moreover, the presence of high residual correlation affects the ordering, which explains the selection of this study to depend on Stata programmes, as applied by Abrigo and Love (2016) for the estimation of panel VAR model[2]. Meanwhile, the Helmert transformation has been used to address the issue of orthogonality[3]. The cross-equation hypothesis testing also becomes more straightforward with the combined assessment of the system of equations. This study has used the Granger causality Wald test based on the GMM estimation and related covariance matrices; thus, testing the hypothesis that propounds the notion that all coefficients on the lag of variable m are zero in the equation for variable n.

Obtaining an estimation for the relationship between CSR and CPA is a challenging task because the endogenous and exogenous factors have influences on each other. Determining the effect of one factor over another and analysing the impacts of various factors are difficult. This study addressed this issue by using Panel VAR. This procedure was developed by Abrigo and Love (2016)[4]. The basis of this program is the framework for a Generalised Method of Moments (GMM). Panel VAR is a type of model that is highly relevant to the concurrent condition model. Furthermore, it can be used to empirically differentiate the transmission mechanisms of macroeconomic and financial variables to economic activity. Using orthogonal response functions (impulse response function, which will be referred to hereafter as IRF) addresses the previously

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[1] Abrigo & Love (2016) applied the first generation GMM estimator, which was proposed by Anderson & Hsiao (1982) in order to address the Nickell bias (Nickell, 1981).

[2] Love & Zicchino (2006) developed Stata programmes, which allow the estimation of panel VAR model and the calculation of impulse response functions. Accordingly, this study adopted the improved version (Abrigo & Love 2016).

[3] $y_{i,t+1}^{\perp} + 1 = c_{i,t}(y_{i,t} - 1/T_{i,t} \sum_{s>t} y_{i,s})$, where $c_{i,t} = \sqrt{T_{i,t}/(T_{it} + 1)}$. Arellano & Bover (1995) recommended such transformation to minimize the data losses due to data gaps.

[4] Abrigo & Love (2016) use the first generation GMM estimator suggested by Anderson & Hsiao (1982) to deal with the Nickell bias (Nickell, 1981).

discussed and specified issue. As a rule, one variable's reaction (e.g. CSR) may generate a shock in another variable (e.g. an accurate assessment, estimation, and evaluation of CPA can be obtained by keeping the basic model's every single other variable consistent and by disregarding their progressions (shock)).

This study makes use of the Panel VAR modelling using information from the period of 2007 to 2016 to illustrate the interactions between corporate political activity (CPA) and corporate social responsibility (CSR). The estimation of Panel VAR helps integrate VAR's advantages (one can assume that all variables are endogenous) and the advantages of utilising panel data. Thus, it makes it possible to evaluate the firm's individual heterogeneity (Love and Zicchino, 2006). Thus, we have assessed the Panel VAR models CSR-CPA model to illustrate the parameters and test if the models' coefficients satisfy the hypothetical desires and suppositions. All the arrangements have been inferred using the Thomson Reuters DataStream to procure the accurate database. Furthermore, STATA 14 was used to lead the experimental exercise. Based on the current empirical literature, the relationship of CSR-CPA has been modelled in the bivariate framework based on the following structure:

$$\textit{Corporate Social Responsibility} = f \; (\textit{Corporate Political Activity}) \tag{1}$$

Based on the above information, direction of causality and long-term equilibrium relation were studied using techniques that deal with cross-sectional dependence. The departure of panel data analysis' point depends on the direct and linear panel data regression model. This is demonstrated below:

$$CSR_{it} = \alpha + \beta CPA_{it} + \varepsilon_{it} \tag{2}$$

Here, CSR_{it} and CPA_{it} stand for the model's dependent and independent variables, respectively. Furthermore, the i and t subscripts refer to the 1, 2... N cross-sections while t =1, 2,…T are used to refer to the T time periods. The coefficients for the model (α and β) that was specified in (2) do not have any subscripts because they will be kept constant for all the tests and units. Lastly, ε_{it} represents the panel data model's error term in (2). Assuming that there are no variations among the information frameworks for the cross-sectional measurement of N, one can evaluate the model (1) using the pooled OLS technique and while utilising a typical steady for every cross-section (Asteriou and Hall, 2007). For the panel data model in (1), the error term is critical because it determines if one can estimate the panel data model with fixed or random effects. The assumption for a fixed effects model is that the error term has a non-stochastic variation over i and t. Alternatively, in a random effects model, one assumes that the error differs stochastically. Therefore, model types similar to (1) can be estimated with the use of a pool object.

Panel VARs have a structure that is indistinguishable from VAR models. In other words, all factors are considered endogenous and related. However, a cross-sectional measurement is also integrated into the portrayal. The Panel VAR models illustrated in (3) can be mutually evaluated with the fixed effects or could also be evaluated independently of the fixed effects after they undergo a few transformations using ordinary least square (OLS).

$$Y_{i,t} = Y_{i,\,t-1}A_1 + Y_{i,\,t-2}A_2 + Y_{i,\,t-p+1}A_{p-1} + Y_{i,\,t-p-1}A_p + X_{i,\,t}B + u_i + e_{i,t} \tag{3}$$
$$i \in \{1,2,…100\}, t \in \{2007,…2016\}$$

Where $Y_{i,t}$ represents the (1 x k) vector for the dependent variables; $X_{i,t}$ represents a (1 x I) vector for the exogenous covariates; u_i and $e_{i,t}$ are (1 x I) vector of the dependent variable-specific panel fixed effects and the idiosyncratic errors, respectively. Furthermore, the (k x k) matrices A_1, A_2…, A_{p-1}, A_p and the (I x k) matrix B represent parameters that need to be estimated. It is assumed that the innovation possesses the following characteristic:

$$E[e_{it}] = 0, \; E[e'_{it}e_{it}] = \textstyle\sum \text{ and } [e'_{it}e_{it}] = 0 \text{ for all } t > s.$$

The previously mentioned parameters may be jointly estimated with fixed effects or independently estimated without the fixed effect after utilising the equation-by-equation ordinary least squares (OLS) to transform them. However, the existence of the lagged dependent variables on the system of equations' right-

hand side would bias the estimates d even if the N is large (Nickell, 1981)[5]. Furthermore, even if the bias nears zero as T increases, the simulations conducted by Judson and Owen (1999) revealed that a significant bias was present even when T = 30.

A study by Abrigo and Love (2016) confirms that the equation-by-equation GMM estimation method generates predictable Panel VAR estimates. They also showed that efficiency gains may be achieved if the model is evaluated as a system of equations (Holtz-Eakin, Newey and Rosen, 1988). They made the assumption that the regular set of $L \geq kp + l$ instruments is provided by the row vector Z_{it}, where X_{it} and $\in Z_{it}$ are equations that are indexed using a number in superscript. Their proposal was the following panel VAR model that was transformed based on equation (1). However, they presented it in a more compact structure:

$$
\begin{aligned}
Y_{it}^* &= \overline{Y_{it}^*} \, A + e_{it}^* \\
Y_{it}^* &= [Y_{it}^{1*} \; Y_{it}^{2*} \; ... . \; Y_{it}^{K-1*} \; Y_{it}^{K*}] \\
\overline{Y_{it}^*} &= [Y_{it-1}^* \; Y_{it-2}^* \; ... . \; Y_{it-P+1}^* \; Y_{it-P}^{K*} \; X_{it}^* \;] \\
e_{it}^* &= = [e_{it}^{1*} \; e_{it}^{2*} \; ... . \; e_{it}^{K-1*} \; e_{it}^{K*}] \\
A' &= [A_1' \; A_2' \; ... . A_{P-1}' \; A_P' \; B']
\end{aligned}
\tag{4}
$$

Suppose that the observations are stacked over panels and then stacked over time. The following generates the GMM estimator.

$$
A = (\overline{Y^{*'}} \, Z \, \hat{W} \, Z\overline{Y^*})' \, (\overline{Y^{*'}} \, Z \, \hat{W} \, Z'Y^*)
\tag{5}
$$

Where $\hat{W}$ represents a (L x L) weighting matrix that is assumed to be symmetric, non-singular, and positive semi-definite. If we assumed that $E[Z'e] = 0$ and the rank $E[(\hat{Y}^{*'} \hat{Z}] = kp+l$, one can get a consistent GMM estimator. Furthermore, the weighting matrix $\hat{W}$ may be chosen for efficiency maximisation (Hansen, 1982).

When systems of equations are jointly estimated, the testing of the cross-equation hypothesis becomes straightforward. One can implement the Wald tests on the parameters based on A's GMM estimate and its covariance matrix. Likewise, Granger causality tests may also be performed using this test, as long as it is hypothesised that the lag of variable m's every coefficient are jointly zero in the equation using variable n. In most econometric regressions causality is difficult to discuss. For example, the importance of the coefficient β within the regression will only demonstrate the 'co-occurrence' of x and y. It will not illustrate that x causes y. Thus, the regression will usually only reveal that there some sort of 'relationship' exists between x and y. However, it does not reveal the nature of the relationship, or if x causes y or y brings about x (Granger, 1980).

Abrigo and Love (2016) verified that stable conditions for Panel VAR models imply that such systems are invertible and present infinite-order vector moving-averages (VMA), provided accepted interpretations of estimates via the impulse-response function (IRF). Absent the loss of generality, every exogenous variable in the equations is dismissed, emphasising the autoregressive arrangement of Panel VAR represented in equation (3). Lütkepohl (2005) and Hamilton (1994) demonstrated that VAR models possess stability, if every moduli of their companion matrices $\bar{A}$ strictly present values lower than one, such that each companion matrix is described as:

$$
\bar{A} =
\begin{bmatrix}
A_1 & A_2 & ... & A_P & A_{P-1} \\
I_K & 0_K & ... & 0_K & 0_K \\
0_K & I_K & ... & 0_K & 0_K \\
.. & .. & ... & .. & .. \\
0_K & 0_K & ... & I_K & 0_K
\end{bmatrix}
\tag{6}
$$

The basic impulse-response function Φ_i is processed by modifying the modelled equation as an infinite-order vector moving-average, such that Φ_i presents the VMA parametric values.

$$
\Phi_i =
\begin{cases}
I_k, & i = 0 \\
\sum_{j=i}^{i} \Phi_{t-j} A_j, & i = 1/2 ....
\end{cases}
\tag{7}
$$

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[5] The Nickell bias disappears, if T → ∞. However, for small T various studies confirm that the bias is severe (Phillips & Sul, 2007).

As the instabilities u_{it} correlate simultaneously, stochastic shocks to single variables have a tendency to be supplemented by shocks in others, preventing an inference to explanations involving causality. Nevertheless, the imposition of Cholesky [6] ordering enables decomposition $\Sigma_e= P'P$, wherein P similarly denotes lower-triangular matrices. Disturbances may then be orthogonalised as $P^{-1}e_{it}$ (with covariance matrix $P^{-1}\Sigma_e(P^{-1})'=I_k$), transforming them moving average (MA) parameters into orthogonalised impulse-response values, Φ_iP. In this manner, shocks to single variables will separately produce dynamic responses in every other variable of the model. Impulse-response values are obtained together within 5% and 95% percentile bounds, which are modelled via Monte Carlo simulation modelling involving 200 to 1000 repetitions. Consequently, where zero lines emerge outside confidence bands, evidence is present of statistically meaningful responses to inflicted shocks.

Similarly stable conditions are necessary for forecast-error variance decomposition (FEVD). Confidence intervals can be analytically developed or estimated through a variety of re-sampling methods. FEVD measures of the influence of innovation are represented through variable k upon variable i (Lutkepohl, 2005)[7]. This technique provides measurements of the fractional error in forecast variable i following h intervals, which can be attributed to orthogonal innovation as denoted by variable k. Therefore, FEVD is continually based on the selection of P, entailing specific orderings as well as lags on every relevant variable, for the initial variable concurrently necessarily influences every other variable. In the instance of the first order, profitability measures are treated as the most exogenous, conversely diversification measures are treated as most endogenous (Campa and Kedia, 2002; Villalonga, 2004). Orderings may be sensitive in such cases wherein high residual correlations are present. In this study, we implemented STATA programmes as applied by Abrigo and Love (2016), in order to approximate Panel VAR models[8]. They had proposed Helmert transformations for resolving the problem of orthogonality[9]. Collaborative assessment of the modelled equation system allows for uncomplicated tests of the cross-equation hypotheses. Wald testing of parametric values may be applied in accordance with GMM estimations of A (equation 5) and associated covariance matrices. Granger causality testing of hypotheses that hold every coefficient on lag present in variable m to be jointly zero, within equations for variable n, may be conducted similarly with the use of these tests.

SAMPLE DATA

This study sampled the top 100 WMAC based on a certain criteria. Firstly, the selected organisations were listed in the February 2017 issue of Fortune for the "World's Most Admired Companies", which comprised of 323 organisations based on the ratings in 2016 considering that the Fortune survey was conducted during the fall of the year prior to publication of the issue. Secondly, the organisations were listed in the Fortune list for 10 consecutive years since 2007. This study acquired the CPA data produced by the Centre for Responsive Politics (CRP), which included the mandated public disclosure of lobbying expenditures.

EMPIRICAL ANALYSIS AND RESULTS

Data description

Table 1 presents the results of descriptive statistics, while Table 2 provides the results of correlation coefficients. It is worth noting that the correlation between CSR and CPA was significant. Thus, this study proceeded with the selection tests according to Roodman (2009).

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[6] see Love and Zicchino (2006)

[7] As described in Lütkepohl (2005), if every eingenvalue in A(l) is less than 1 in modulus, than B(l) will satisfy the stability condition and be invertible.

[8] A Stata program, built by Love and Zicchino (2006) allows the estimation of Panel VAR model and the calculation of impulse-response functions. In this paper we use an improved version (Abrigo and Love 2016).

[9] $y_{i,t+1}^{\perp} + 1 = c_{i,t}(y_{i,t} - 1/T_{i,t} \sum_{s>t} y_{i,s})$. Where $c_{i,t} = \sqrt{T_{i,t}/(T_{it} + 1)}$. This transformation is suggested by Arellano & Bover (1995) to minimize data losses due to data gaps.

Table 1 Results of descriptive statistics

Variable	Unit of measurement	Observations	Mean	Standard deviation	Minimum value	Maximum value
lncsr	Log of total scores (scale of 0 to 10)	1000	1.893	0.112	1.386	2.151
lncpa	Log of total amount of lobbying expenditures	867	7.624	1.557	0.000	10.63

Note: All statistics were based on the original data values.

Table 2 Results of correlation coefficients

	lncsr	lncpa
lncsr	1	
lncpa	0.120***	1

Notes: * denotes statistical significance at 10% level; ** denotes statistical significance at 5% level; *** denotes statistical significance at 1% level.

As shown in Table 3, this study employed the first- to third-order panel VAR with using the first five lags of CSR and CPA as instruments are shown table 3 to calculate the selection measures. According to the established criteria by Andrews and Lu (2001) and Abrigo and Love (2016) in reference to the moment and model selection criteria (MMSC) and the overall coefficient of assurance (CD), this study selected the first-order panel VAR model among the three models based on the minimum values presented for the Bayesian information criterion (MBIC), the Akaike information criterion (MAIC), and the Hannan-Quinn information criterion (MQIC).

Andrews-Lu Model Selection Procedure
Table 3 presents a range of descriptive statistics, while we report the correlation coefficients in Table 4. It is worth noting that all CPA variables exhibit a significant correlation with the CSR. Selection tests can be carried out by following the approach of (Roodman, 2009). Among the significant assumptions that must be established is the strength of the GMM estimator, if every instrument in the system was to be regarded as exogenous. In the case of over-identification, the Hansen J-Test (Hansen, 1982)[10] is automatically dismissed from the GMM framework. Tests can be utilised in single-step (Λ_Z) and dual-step ($\Lambda_{Z\hat{e}}$) GMM estimations

$$\left[\sum_{i=1}^{N} Z_i \ \widehat{E_i}\right]^{\mathrm{T}} \Lambda_{Z\hat{e}}^{-1} \left[\sum_{i=1}^{N} Z_i \ \widehat{E_i}\right] a \ \widetilde{X_{L\_K}^2} \tag{8}$$

Andrews and Lu (2001) presented a class of moment and model selection criteria (MMSC) that poses similarities to the outstanding-model segment criterion for selection among competing schemes. As originally presented in the report by Andrews and Lu (2001), basic MMSC equations can be presented as:

$$\text{MMSC}_n(b, c) = J_n(b, c) - h(|c| - |b|)K_n \tag{9}$$

Wherein $J_n(b,c)$ denotes the Hansen J test measurement values from Eq. (8), such that b continues to signify the quantities of parameters, c denotes quantities of insignificant conditions, while n signifies the total number of observations. Three different types of MMSC functions were utilised:

$$\text{MMSC}_{BIC,n}(b, c) = J_n(b, c) - (|c| - |b|) \cdot ln(n)$$
$$\text{MMSC}_{AIC,n}(b, c) = J_n(b, c) - (|c| - |b|) \cdot 2$$
$$\text{MMSC}_{HQIC,n}(b, c) = J_n(b, c) - Q \cdot (|c| - |b|) \cdot ln(ln(n)) \tag{10}$$

Andrews and Lu (2001) proposed the application of Bayesian information criteria (MMSC-BIC) as well as Hannan-Quinn information criteria (MMSC-HQIC). Akaike information criteria (MMSC-AIC) cannot meet their standard of consistency given its positive, even asymptotic, probability of selecting for an overly-limited, over-identified set of constraints.

Selection measures were calculated by utilising first-to-third-order panel VAR sets, with instrumented usage of the initial five lags of CSR and CPA, as depicted in Table 5. The findings show the first-order panel VAR to be favoured among the three models subject to testing in accordance with the criteria set by Andrews and Lu (2001) as well as that of Abrigo and Love (2016). This is with reference to moment and model selection criteria (MMSC) and overall coefficient of assurance (CD). First order is picked, for it presents minimum values

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[10] Roodman (2009) provides an excellent discussion of GMM estimation in a dynamic panel setting and its applications using Stata. Readers are encouraged to read his paper for a more detailed discussion of this topic.

for MBIC, MAIC, and MQIC. While there is an additional requirement to constrain the Hansen's J statistic, the procedure cannot correct for degrees of freedom as described in the moment and model selection criterion of Andrews and Lu. The scheme poses a requirement for the values of moment conditions to be larger than the values of the associated endogenous variables. The outcomes of this testing, along with post-estimation testing, validate the first-order model to be more stable than that of other potential systems. Given the analytical criteria, the first-order panel VAR shows a fit with an identically specified set of instruments derived previously, via GMM estimations.

Table 3 Results of panel VAR's optimal moment and model selection criteria selection

Lag	CD	J	J_pValue	MBIC	MAIC	MQIC
1	0.987	20.301	0.061	-51.976	-3.694	-22.790
2	0.970	15.744	0.046	-32.443	-0.256	-12.987
3	0.977	4.030	0.401	-20.064	-3.670	-10.335

Referring to the eigenvalues (below one) in the estimated model, the panel VAR model was found to satisfy the stability condition that presents invertibility and infinite-order VMA. Both Brüggemann et al. (2006) and Hamilton (1994) implicated VAR stability in every instance wherein every modulus in the companion matrices returned values lower than one refer to table 4 and figure 1.

Table 4 Results of eigenvalue stability condition

Eigenvalue		Modulus
Real	Imaginary	
0.618	0	0.618
-0.239	0	0.239

Notes: All eigenvalues were within the unit circle; thus, the panel VAR model satisfied the stability condition.
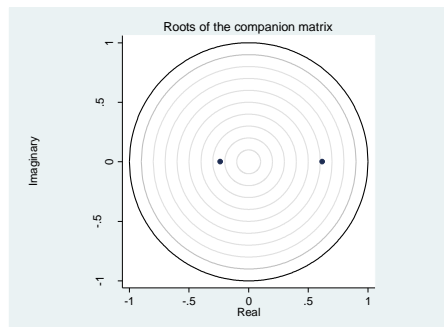

Figure 1 Graph of Eigenvalues within the Unit Circle

Panel VAR and Granger causality Wald test

Using the GMM-style instruments, the obtained coefficients in the panel VAR model for CSR and CPA are revealed in Table 5. The relationship between CSR and CPA was found to be significantly negative at the 5% level, which reaffirmed the negative effect of CSR on CPA. In addition, the inverse bidirectional causal relationship between CPA and CSR may be plausible considering that CPA was found to affect CSR negatively at the 1% level. Meanwhile, Table 6 presents the results from the Granger causality Wald test, which revealed that CSR did Granger-cause CPA and CPA Granger-caused CSR, as well. These results verified the bidirectional causal relationship between CSR and CPA.

Table 5 Main results of 2-variables panel VAR model

	Model 1	
	(1)	(2)
Variable	lncpa	lncsr
$lncpa_{t-1}$	0.013*	-0.060***
	(0.141)	(0.016)
$lncsr_{t-1}$	-2.581***	0.365***
	(1.037)	(0.141)
Observations	672	672
Number of panels	87	87

Notes: The standard errors are reported in parentheses (p-values). Meanwhile, * denotes statistical significance at 10% level; ** denotes statistical significance at 5% level; * denotes statistical significance at 1% level.

Table 6 Results of bivariate panel VAR-Granger causality Wald test

Null Hypothesis	Observations	Chi^2	p-value
CSR does not Granger cause CPA	672	13.764	0.000
CPA does not Granger cause CSR	672	6.197	0.013

Notes: * denotes statistical significance at 10% level; ** denotes statistical significance at 5% level; *** denotes statistical significance at 1% level.

This study obtained the inferred FEVD and IRF for the determination of causal ordering (Abrigo and Love, 2016). The confidence intervals and the standard errors for the FEVD estimates were similar, wherein the detailed results are not provided to conserve space (available upon request). Meanwhile, as for the calculation of the IRF confidence intervals, this study adopted 200 Monte Carlo simulations. As shown in Table 7, CPA explained as much as 16.7% of variance in CSR whereas CSR explained 12.9% of variance in the future CPA based on the FEVD estimates.

Table 7 Results of forecast error variance decompositions (FEVD)

Forecast horizon	Impulse lncsr	Variable lncpa
lncsr		
0	0	0
1	1	0
2	0.849721	0.150279
3	0.840473	0.159527
4	0.833271	0.166729
5	0.831237	0.168763
6	0.830382	0.169618
7	0.830070	0.169930
8	0.829949	0.170051
9	0.829903	0.170097
10	0.829886	0.170114
lncpa		
0	0	0
1	0.008096	0.991904
2	0.113825	0.886175
3	0.122129	0.877871
4	0.128610	0.871390
5	0.130518	0.869482
6	0.131320	0.868680
7	0.131614	0.868386
8	0.131728	0.868272
9	0.131772	0.868229
10	0.131788	0.868212

Note: The FEVD standard error and confidence intervals are based on 200 Monte Carlo simulations.

Apart from that, Figure 2 presents the results of IRF in this study, which demonstrated the IRF of CSR, given the innovative activities in CPA. The following interpretations of these obtained results are based on the notion that the errors terms are not associated. In terms of levels, the negative shock on CPA increases the CSR engagement, which exhibits inward bending CSR engagement and CPA. Additionally, the shock in CPA contributes to short-lived negative effect on the CSR engagement, which reaffirms the causal direction from CPA towards CSR in the relationship of CSR and CPA.
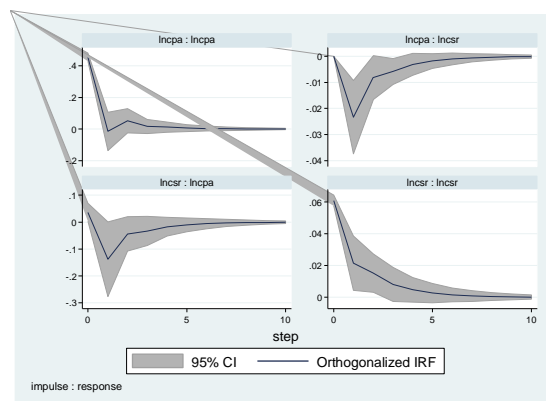

Figure 2 Functions of Impulse Responses

CONCLUSIONS

This study presented the dynamic causality between CSR and CPA based on a comprehensive dataset using the panel VAR model. Specifically, the selected approach in this study took into account the firm-specific fixed-effects and focused on the impulse response analysis in assessing the effect of shock to CSR on CPA. Additionally, this study performed the variance decomposition to assess the significance of these effects. The resultant outcomes of this study contradicted the notion propounded by the hypothesis of virtuous circle that there is a positive relationship and mutual reinforcement between CSR and CPA. The resultant outcomes of this study are twofold. Firstly, this study demonstrates the negative effect of the shock to CSR on CPA. Secondly, this study reveals that the short-term negative effect of CSR on CPA is significant, and the observed congruous relationship reaffirmed the potential extension of the effect for more than 10 years with respect to the negative synergy hypothesis (wherein the socially responsible organisations have lower political influence and stakeholder trust, limiting their socially responsible investments).

REFERENCES

Abrigo, M.R. and Love, I. (2016) Estimation of panel vector autoregression in Stata. *Stata Journal*. 16 (3), pp. 778-804.

Anastasiadis, S. (2014) Toward a view of citizenship and lobbying: Corporate engagement in the political process. *Business and Society*. 53 (2), pp. 260-299.

Anderson, T.W. and Hsiao, C. (1982) Formulation and estimation of dynamic models using panel data. *Journal of econometrics*. 18 (1), pp. 47-82.

Andrews, D.W. and Lu, B. (2001) Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics*. 101 (1), pp. 123-164.

Arellano, M. and Bover, O. (1995) Another look at the instrumental variable estimation of error-components models. *Journal of econometrics*. 68 (1), pp. 29-51.

Asteriou, D. and Hall, S.G. (2007) *Applied econometrics: A modern approach using eviews and microfit revised edition*. Palgrave Macmillan.

Beloe, S. and Harrison, J. (2007) *Coming in from the cold: Public affairs and corporate responsibility*. SustainAbility Limited.

Bendell, J. and Kearins, K. (2005) The political bottom line: the emerging dimension to corporate responsibility for sustainable development. *Business Strategy and the Environment*. 14 (6), pp. 372-383.

Brüggemann, R., Lütkepohl, H. and Saikkonen, P. (2006) Residual autocorrelation testing for vector error correction models. *Journal of Econometrics*. 134 (2), pp. 579-604.

Campa, J.M. and Kedia, S. (2002 Explaining the diversification discount. *The Journal of Finance*. 57 (4), pp. 1731-1762.

Caulkin, S. and Collins, J. (2003) T*he private life of public affairs*. London: Green Alliance.

Doh, J.P., Lawton, T.C. and Rajwani, T. (2012) Advancing nonmarket strategy research: Institutional perspectives in a changing world. *The Academy of Management Perspectives*. 26 (3), pp. 22-39.

Getz, K.A. (1997) Research in corporate political action: Integration and assessment. *Business and Society*. 36 (1), pp. 32-72.

Granger, C.W. (1981) Some properties of time series data and their use in econometric model specification. *Journal of econometrics*. 16 (1), pp. 121-130.

Hamilton, J.D. and Susmel, R. (1994) Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics*. 64 (1-2), pp. 307-333.

Hansen, L.P. (1982) Large sample properties of generalized method of moments estimators. *Econometrica*. pp. 1029-1054.

Hillenbrand, C., Money, K. and Ghobadian, A. (2013) Unpacking the mechanism by which corporate responsibility impacts stakeholder relationships. *British Journal of Management*. 24(1), pp. 127-146.

Hillman, A.J. and Hitt, M.A. (1999) Corporate political strategy formulation: A model of approach, participation, and strategy decisions. *Academy of Management Review*. 24 (4), pp. 825-842.

Hillman, A.J., Keim, G.D. and Schuler, D. (2004) Corporate political activity: A review and research agenda. *Journal of Management*. 30 (6), pp. 837-857.

Holtz-Eakin, D., Newey, W. and Rosen, H.S. (1988) Estimating vector autoregressions with panel data. *Econometrica*. pp. 1371-1395.

Hond, F., Rehbein, K.A., Bakker, F.G. and Lankveld, H.K.V. (2014) Playing on two chessboards: Reputation effects between corporate social responsibility (CSR) and corporate political activity (CPA). *Journal of Management Studies*. 51 (5), pp. 790-813.

Judson, R.A. and Owen, A.L. (1999) Estimating dynamic panel data models: a guide for macroeconomists. *Economics letters*. 65 (1), pp. 9-15.

Lin, K.J., Tan, J., Zhao, L. and Karim, K. (2015) In the name of charity: political connections and strategic corporate social responsibility in a transition economy. *Journal of Corporate Finance*. 32, pp. 327-346.

Love, E.G. and Kraatz, M. (2009) Character, conformity, or the bottom line? How and why downsizing affected corporate reputation. *Academy of Management Journal*. 52 (2), pp. 314-335.

Love, I. and Zicchino, L. (2006) Financial development and dynamic investment behavior: Evidence from panel VAR. *The Quarterly Review of Economics and Finance*. 46 (2), pp. 190-210.

Luo, Y. (2006) Political behavior, social responsibility, and perceived corruption: A structuration perspective. *Journal of International Business Studies*. 37 (6), pp. 747-766.

Lütkepohl, H. (2005) *New introduction to multiple time series analysis*. Springer Science and Business Media.

Matten, D. and Crane, A. (2005) Corporate citizenship: Toward an extended theoretical conceptualization. *Academy of Management Review*. 30 (1), pp. 166-179.

Nickell, S. (1981) Biases in dynamic models with fixed effects. *Econometrica*. pp. 1417-1426.

Peterson, K. and Pfitzer, M. (2009) Lobbying for good. *Stanford Social Innovation Review*. 7 (1), pp. 44-49.

Post, J.E., Murray, E., Rickie, R.B. and Mahon, J. F. (1983) Managing public affairs. *California Management Review*. 26, pp. 135–50.

Rehbein, K. (2015) The Payoff from Corporate Social Responsibility in China: Does the Political Context Matter? *Academy of Management Perspectives*. 29 (3), pp. 1–3.

Rehbein, K. and Schuler, D.A. (2013) Linking corporate community programs and political strategies: A resource-based view. *Business and Society*. 54 (6), pp. 794-821.

Roodman, D. (2009) A note on the theme of too many instruments. *Oxford Bulletin of Economics and statistics*. 71 (1), pp. 135-158.

Scherer, A.G. and Palazzo, G. (2007) Toward a political conception of corporate responsibility: Business and society seen from a Habermasian perspective. *Academy of Management Review*. 32 (4), pp. 1096-1120.

Scherer, A.G. and Palazzo, G. (2011) The new political role of business in a globalized world: A review of a new perspective on CSR and its implications for the firm, governance, and democracy. *Journal of Management Studies*. 48 (4), pp. 899-931.

Villalonga, B. (2004) Does diversification cause the" diversification discount"?. *Financial Management*. pp. 5-27.

Wang, H. and Qian, C. (2011) Corporate philanthropy and corporate financial performance: The roles of stakeholder response and political access. *Academy of Management Journal*. 54 (6), pp. 1159-1181.

Werner, T. (2015) Gaining access by doing good: The effect of sociopolitical reputation on firm participation in public policy making. *Management Science*. 61 (8), pp. 1989-2011.