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The Market Value of Corporate Social Performance in BRICS Countries: Differential Results Based on Panel Data Methods

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Abstract
Although the causal effect of social performance on financial performance is a critical issue for companies and their stakeholders, there has been no consistent econometric approach in the relevant literature to examine this relationship yet. From this point of view, the main motivation of this study is twofold: first, it aims to reveal the differential results of static and dynamic panel data methods used to estimate the impact of corporate social performance (CSP) on corporate financial performance (CFP). Second, in order to take the initiative for a consistent and reliable estimation method of the causal relationship between CSP and CFP, this study aims at drawing attention to the challenges of system generalized method of moments, which is suggested as an efficient method to solve the endogeneity problem in dynamic models. To this end, the impact of CSP on CFP for a sample of BRICS countries was analyzed through both static and dynamic panel data specifications. The main results reveal that static panel data models estimated with pooled OLS, random and fixed effects result in inconsistent and biased parameter estimates. This study discusses that although the two-step system GMM is suggested as a reliable method to deal with the endogeneity issue, some critical specifications should be considered while utilizing this method to achieve robust and efficient results.

Keywords: Corporate Social Performance, Two-Step System GMM, Static Panel Data, Dynamic Panel Data, BRICS Countries

Businesses, as open systems, interact with the environment in which they operate by utilizing resources from and producing outputs into their environment. Corporate social performance (henceforth, CSP) deals with the positive and negative outcomes of this interaction in terms of not only economic but also other dimensions such as environmental, social, and governance (Wood, 2010). Achieving a satisfying CSP in the eyes of its stakeholders may bring a business several benefits such as easy access to resources, increased employee loyalty, improved brand reputation (Haanaes et al., 2011). On the other hand, it is also argued that the investment in CSP activities means the misallocation of resources since it is not in investors' best interest (Aupperle et al., 1985). These contradicting views on the CSP activities of businesses have stimulated the researchers to investigate the impact of CSP on corporate financial performance (henceforth, CFP).

The causal link between CSP and CFP has been examined through many academic studies without a uniform conclusion. Different proxy variables used to measure CSP and CFP, diversity in sample and time frame of the studies, ignoring endogeneity are some of the factors which have been cited as the reasons behind the inconsistencies in the inferences of the researches on this issue (Brooks & Oikonomou, 2018). However, aside from the studies dealing with different samples, it is possible to obtain different results even within a single study. The main cause of this inconsistency is different methods applied to estimate the model developed to reveal the link between CSP and CFP.

Although the causal effect of social performance on financial performance is a critical issue for companies and their stakeholders, there has been no consistent econometric approach to examine this relationship yet. While most of the studies conducted static panel data methods with pooled OLS, random or fixed effects estimators (e.g. Buallay, 2019a, 2019b, 2019c; Minutolo et al., 2019; Miralles-Quirós et al., 2019; Park et al., 2018) fewer researches utilized dynamic panel data methods (Deng & Cheng, 2019; Nekhili et al., 2019).

Panel data have been widely used to derive causal inferences in social science research, however, it has been argued to confront a range of problems such as specification problems (Kittel & Winner, 2005), endogeneity especially in static panel data models (Semykina & Wooldridge, 2010), lack of robustness across different panel data models (Kittel, 2006) and, so on. When these technical issues are not handled in a reliable manner, they may affect the conclusions based on analyses with panel data (Kittel, 2008).

Leszczensky and Wolbring (2019) reviewed several panel data estimation methods in terms of their exogeneity assumptions and discussed the ways of relax-

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ing exogeneity assumption which does not hold in much of social science research. The authors concluded that pooled OLS and random effects estimators will be biased if the exogeneity assumption is violated due to time-invariant unobserved heterogeneity and reverse causality between independent and dependent variables. Although unobserved heterogeneity does not constitute a problem for fixed effects and first-difference models, reverse causality remains a factor leading to biased estimates since it violates exogeneity assumption of the mentioned models. The authors demonstrate that although lagged first difference model prevents biases caused by both unobserved heterogeneity and reverse causality, it suffers from bias if the effect of independent variables on the dependent variable is fully lagged. Finally, they reviewed dynamic panel data models including the generalized method of moments (GMM) and cross-lagged panel model with fixed effects as the more reliable methods to prevent bias due to reverse causality. Based on the Monte-Carlo simulations they conducted, the authors suggested that researchers utilize a cross-lagged panel model with fixed effects in the case of reverse causality since it enables to overcome the problems caused by the misspecification of temporal lags. Like Leszczensky and Wolbring (2019), Allison et al. (2017) revealed that the cross-lagged panel model with fixed effects is less biased than the GMM model. However, they also pointed out that a cross-lagged panel model with fixed effects may be problematic in the cases of serial correlation and unbalanced panel. In this study having an unbalanced panel dataset, we tried to achieve a more reliable GMM estimation utilizing the sequential model selection process of Kripfganz (2019) and using the Stata command "xtdpdgmm" instead of "xtabond2" which has been claimed to have inaccurate aspects and some bugs (Kiviet, 2020; Kripfganz, 2019).

To our knowledge, there is a limited number of studies investigating the impact of the panel data estimation method on the inference regarding the nexus between CSP and CFP. Garcia-Castro et al. (2010) especially focused on the issue of endogeneity. Using the KLD index as the proxy for CSP and four measures of CFP, namely ROA, ROE, Tobin's Q, and MVA, the authors compared the results of pooled OLS, fixed effect, and instrumental variables (IV) estimation methods and suggested IV to deal with endogeneity. Elsayed and Paton (2005), more similar to this study, revealed the differential results of static and dynamic panel data methods applied to estimate the models investigating the impact of environmental performance on financial performance. Both studies have a sample of firms from developed countries, the US and the UK, respectively. Using a sample of 28 air carriers from various countries, Lahouel et al. (2019) emphasized the convenience of the dynamic system generalized method of moments (GMM) estimator comparing it with other estimators such as fixed effects, GLS, fixed effects instrumental variables, and two-stage least squares methods. Lin et al. (2019) compared the results of pooled OLS, fixed effect, and system GMM while examining the relationship between CSP and CFP.

Although these studies highlight the GMM as a more efficient method to estimate the effect of CSP on CFP, the GMM estimator has its challenges which have not been addressed in the mentioned studies but can bias the results significantly unless handled correctly. None of the mentioned studies include a model selection process to find the most efficient and consistent model specification for GMM estimation. They simply add the one-year lagged dependent variable in the GMM model, however, a model selection process would result in a more efficient and consistent model specification including further lags of the dependent variable and also explanatory variables. Additionally, the classification of regressors as endogenous, predetermined, or exogeneous has not been discussed in the mentioned studies although this classification would have significant effects on the results of GMM estimation. Finally, the Stata command (xtabond2) for GMM estimations used in these studies (Lahouel et al., 2019; Lin et al., 2019) has been proven to have some bugs when dummies with factor notation are included in the model and forward orthogonal deviations are used (Kripfganz, 2019; Kiviet, 2020). To sum up, the existing studies investigating the impact of the panel data estimation method on the inference regarding the nexus between CSP and CFP have just compared the results of GMM with other estimation methods without addressing the challenges of GMM estimator which may bias the results significantly unless handled correctly. The main motivation of this study is to fill in this gap and raise awareness of these challenges for the empirical studies testing the impact of CSP on CFP and take the initiative for a consistent and reliable estimation method to be applied in the studies on this specific issue. In accordance with this motivation, this research investigates the effect of CSP on CFP for a sample of BRICS countries representing a group of emerging markets with a strong prospect of economic growth. Utilizing both static and dynamic panel data models, pooled OLS, fixed effects, random effects, and two-step system GMM methods were applied and differential results of these methods were revealed. Finally, the two-step system GMM was suggested as the most reliable method along with some critical specifications to be considered while utilizing this method.

The contribution of this study to the literature is fourfold: First, this study reveals the differential results based on the estimation method used even in the same dataset. Second, using dynamic panel data estimation methods clarifies the dynamic and long-run relationship between CSP and CFP. Third, this study clarifies the critical factors researchers should consider while applying system GMM as a dynamic panel data estimation method. Finally, having a sample of BRICS countries, this study enriches the extant literature for emerging countries.

The remaining part of the paper proceeds as follows: The next section discusses the relevant literature. While *Research Methodology* is concerned with the research design, *Results* presents the findings of the research. A summary of the research, implications of the findings, and limitations of the study are given in *Conclusion*.

Literature Review

The literature review of this study aims to focus attention on the different estimation methods employed in academic studies investigating the link between CSP and CFP. Towards this purpose, the framework of the literate review has been determined with some limitations. The mentioned framework covers the articles indexed in the Web of Science over the last two years (2018-2019) and which used, in at least one of its research models, TOBIN'S Q and ESG SCORES&DISCLOSURE as the proxies for CSP and CFP, respectively.

Table 1, which summarizes the reviewed literature, displays the diversity of panel data estimation methods applied to estimate the link between TOBIN'S Q and ESG SCORES&DISCLOSURE. It should be noted that in some studies, ESG scores were used as a measure of sustainability performance (Aboud & Diab, 2018; Ionescu et al., 2019; Miralles-Quirós et al., 2019; Nekhili et al., 2019; Park et al., 2018) while others use ESG disclosure level as a proxy for transparency or CSR activities (Atan et al., 2018; Buallay, 2019a; 2019b; 2019c; Chauhan & Kumar, 2018; Kim et al., 2018; Li et al., 2018; Minutolo et al., 2019; Yu et al., 2018) Some studies used both types of measurements in a single study (Fatemi et al., 2018).

All the studies listed in Table 1 investigate the relationship between CSP and CFP which has been suggested to be endogenous. This endogeneity is mainly due to the fact that managers' decisions about corporate social responsibility activities just like other strategic decisions are not independent of their anticipation of the financial effect of those decisions (Garcia-Castro et al., 2010; Hamilton & Nickerson, 2003). While a solution for the endogeneity problem in the models with Tobin's Q as dependent and ESG scores/disclosures as the independent variable was not mentioned in some studies (Aboud & Diab, 2018; Atan et al., 2018; Ionescu et al., 2019; Minutolo et al., 2019; Miralles-Quirós et al., 2019; Park et al., 2018; Yu et al., 2018) on Table 1, some claimed that country-level control variables were used to deal with the endogeneity issue (Buallay, 2019a; 2019b; 2019c). More reliable estimation methods to solve the endogeneity problem such as the two-stage least squares method (Chauhan & Kumar, 2018; Fatemi et al., 2018; Li et al., 2018) and two-step GMM (Kim et al., 2018; Nekhili et al., 2019) were used in just a few studies listed on Table 1. However even in most of the studies applying more reliable methods for endogeneity, lagged dependent variable (i.e. TOBIN'S Q value of previous year) was not included as an independent variable in the research model (Fatemi et al., 2018; Li et al., 2018; Kim et al., 2018).

Table 1 Summary of Literature Review

Study	Sample Data	Sample Year	Estimation Method	Endogeneity Solution	CSP-CFP Relationship
Aboud & Diab (2018)	1.507 observations of the listed firms in the Egyptian stock market	2007-2016	OLS	Not mentioned	Positive
Atan et al. (2018)	162 observations of 54 Malaysian companies	2010-2013	OLS, fixed effects, random effects	Not mentioned	Insignificant
Buallay (2019a)	2,350 observations of 235 listed banks on the European Union countries	2007-2016	Random - effects	Usage of country-level control variables	Positive
Buallay (2019b)	3,420 observations of 342 listed financial institutions from 20 countries	2007-2016	Fixed - effects	Usage of country-level control variables	Positive (only for the model including Tobin's Q as the proxy for CFP)
Buallay (2019c)	7,248 observations of 392 manufacturing companies and 4,457 observations of 530 banks from 80 countries	2008-2017	Random - effects	Usage of country-level control variables	Positive (negative) for manufacturing (banking) sector
Chauhan & Kumar (2018)	3,837 observations of 630 Indian non-financial firms	2007-2016	OLS with industry and year fixed effects	Usage of 2SLS in robustness tests	Positive
Fatemi et al. (2018)	1,640 observations of 403 U.S. listed companies	2006-2011	Two-stage least squares (2SLS)	Usage of 2SLS	Negative (positive) for ESG disclosure & ESG concerns (ESG strengths)
Ionescu et al. (2019)	434 observations of 73 travel and leisure companies listed in S&P Global Broad Market Index Universe	2010-2015	Ordinary Least Squares (OLS)	Not mentioned	Mixed

Study	Sample Data	Sample Year	Estimation Method	Endogeneity Solution	CSP-CFP Relationship
Kim et al. (2018)	250 observations of 48 listed Korean firms	2010-2014	Generalized Method of Moments (GMM)	Usage of two-step GMM	Positive
Li et al. (2018)	2,415 observations of FTSE 350 firms in the UK	2004-2013	OLS, 2SLS, Heckman	Usage of 2SLS and Heckman Methods	Positive
Minutolo et al. (2019)	2,960 observations of 467 firms in the S&P 500	2009-2015	Fixed - effects	Not mentioned	Positive (greatest for large firms as measured by sales)
Miralles-Quirós et al. (2019)	996 observations of 166 banks from 31 countries	2010–2015	OLS	Not mentioned	Positive (negative) for environmental & governance (social) performance
Nekhili et al. (2019)	91 French firms	2007-2017	Two-step system GMM	Usage of two-step system GMM	Mixed
Park et al. (2018)	3,390 observations of firms listed in the Korea Stock Exchange	2012-2017	OLS with industry and year fixed effects	Not mentioned (for the model including Tobin's Q as the dependent variable)	Positive
Yu et al. (2018)	1996 non-financial firms from MSCI All Country World Index	2012-2016	Generalized Least Squares	Not mentioned (for the model including Tobin's Q as the dependent variable)	Positive non-linear

In the models investigating the effect of CSP on CFP, omitting the lagged dependent variable within the independent variables requires an assumption of no correlation between the current and historical values of CFP which is not well-reasoned (Garcia-Castro et al., 2010). Current financial performance, which is the dependent variable of these models, cannot be explained disregarding the feedback from the past realizations of financial performance (Lahouel et al., 2019) since strategic management decisions are highly affected by past financial performance (Garcia-Castro et al., 2010). Past financial performance was also empirically found to explain the variation in current financial performance (e.g. Capkun et al, 2009; Nguyen et al., 2014; Thrikawala, 2017). This correlation between past and present financial performance is just one of the sources of endogeneity problem existing in the static panel data models investigating the causal effect of CSP on CFP.

The reverse causality between CSP and CFP is another factor causing endogeneity bias in the models estimated with pooled OLS, random or fixed effects which are based on an exogeneity assumption (Leszczensky & Wolbring, 2019). CSP has been argued to be "*both a predictor and consequence of firm financial performance*" since it could be that companies achieving a satisfying financial performance have slack resources to invest in social responsibility activities or a better CSP leads to better financial performance due to accompanying results such as enhanced stakeholder relations or increased employee productivity (Waddock & Graves, 1997).

The other sources of endogeneity such as unobserved heterogeneity or inadequate measurements of variables are also valid for the models developed for the causal link between CFP and CSP. Recognizing the endogeneity issue for the studies on the CFP-CSP link, some researchers (Garcia-Castro et al., 2010; Lahouel et al., 2019) have started to utilize econometric models which provide more reliable estimates in the case of endogeneity. These studies showed that the positive and significant relationship between CSP and CFP turns to an insignificant relationship when estimated by a model that addresses the endogeneity issue. Although the number of studies highlighting the endogeneity issue in the research on the CSP-CFP relationship has been increasing recently, the studies emphasizing and providing guidance for the challenges of panel data methods used to solve endogeneity problems are not common. This study aims to guide researchers to handle the challenges of the GMM estimator which has been recently advised to use in the research on the CSP-CFP link (Lahouel et al., 2019).

Research Methodology

Sample

The sample of this study is based on firms from BRICS countries. The initial sample consists of firm-year observations from BRICS countries available at the Datastream database for the period 2009-2018. After eliminating the observations with missing data, the final sample covers an unbalanced panel of 3,687 firm-years. Table 2 presents the classification of this sample by both industry and country. Most of the firm-years in the final sample belong to the firms from South Africa (25.3%) and China (28.4%) and the most observed industries are financials (19.1%) and basic materials (13.7%).

Table 2 Sample Classification by Industry & Country

Industry		Brazil	China	India	Russia	S.Africa	Total N	Total %
Basic Materials		95	98	60	69	182	504	13.7
Consumer Discretionary		106	145	64	3	107	425	11.5
Consumer Staples		82	49	79	11	99	320	8.7
Energy		34	97	43	82	10	266	7.2
Financials		96	232	159	32	186	705	19.1
Health Care		28	68	81	7	39	223	6.1
Industrials		75	169	49	0	140	433	11.7
Real Estate		48	59	32	8	91	238	6.5
Technology		8	37	44	0	34	123	3.3
Telecommunications		33	42	39	36	44	194	5.3
Utilities		110	52	48	46	0	256	6.9
Total	N	715	1,048	698	294	932	3,687	
	%	19.4	28.4	18.9	8.0	25.3		

Data and Variable Description

The dependent variable of the research models in this study was the corporate financial performance which was measured by Tobin's Q ratio. Tobin's Q, which is a market-based measure of CFP, was calculated by the following equation: (Market capitalization + Total Liabilities) / Total Assets. It is defined as "*the ratio between the market value of the firm over the reproduction cost of its assets*" (Lindenberg & Ross, 1981). CFP can also be measured by accounting-based measures such as return on assets, return on equity, return on sales, net profit. However, Tobin's Q, as a market-based measure of CFP, was preferred in this study since unlike accounting-based measures, market-based measures have the ability to capture the value of long-term investments, are less vulnerable to managerial manipulations, are not influenced by firm-specific accounting procedures, and reflect investors' expectation about companies' future economic benefits. Accounting-based measures reflect only the historical performance of companies, are subject to managerial manipulation, and depend on accounting policies adopted by the company (McGuire et al., 1988). Based on these arguments, Tobin's Q as a proxy for the market value of the company was used as the dependent variable of the research models and an accounting-based measure of CFP representing asset profitability of the company (return on assets) was included in the control variables as in many similar studies due to the fact that profitability has known to be a significant determinant of the market value of the company (Hirschey, 1982; Hsu & Jang, 2009; Kim et al., 2018; Minutolo et al., 2019; Miralles-Quirós et al., 2019; Park et al., 2018).

Corporate social performance is the independent variable of main interest in this study and was measured by companies' environmental, social, and governance pillar scores and additionally overall ESG score derived from the ASSET4 database of Datastream. Processing over 400 firm-specific ESG measures gathered from publicly available information, ESG scores measure a company's performance based on 10 main categories such as product responsibility, emissions, human rights, and so on. Among these category scores, resource use, emissions, and environmental innovation scores constitute environmental pillar score; workforce, human rights, community, and product responsibility scores are weighted with specific rates to calculate social pillar score and governance pillar score calculation is based on management, shareholders and CSR strategy scores. Overall ESG Score is a weighted average calculation of all category scores (Thomson Reuters, 2019).

Following the relevant literature, some firm-specific data were included in the regression models as control variables. "ROA" is the return on assets, directly derived from Datastream to measure the profitability of the company. The variable "SIZE" is a proxy for firm size and was calculated as the natural logarithm of assets. "LEV", which was calculated as the ratio of liabilities to assets, was determined as a proxy for financial risk. Finally, “CAPEX” represents the percentage ratio of capital expenditures to sales. Table 3 provides the descriptions and sources of all variables used.

Regression Models and Estimation Methods

Panel data, which include cross-sectional units observed at different periods, have been largely used in the researches investigating the impact of CSP on CFP or vice-versa. Panel data are known to provide several advantages over cross-sectional and time-series data such as allowing to control for unobserved characteristics of cross-sectional units, improvement in accuracy of estimations, reduction of multicollinearity problem, and so on (Baltagi, 2005; Hsiao, 1985). However, panel data have several estimation methods that may or may not be appropriate for the dataset and models handled. In this paper, to explore the effect of CSP on CFP, both static and dynamic regression models were developed and estimated with different estimation methods. In this way, differential results based on the selected regression model specification and estimation method have been revealed.

Static Panel Data Models

The static panel data regression model developed to express the CFP as a function of CSP is as follows:

$$CFP_{it} = \beta_0 + \beta_1 CSP_{it} + \beta_2 X_{it} + a_i + u_{it} \tag{1}$$

where CFP_{it} represents TOBIN’S Q; CSP_{it} is environmental (ENV) or social (SOC) or governance (GOV) or overall (ESG) score of the firm; X_{it} represents control variables (ROA, SIZE, LEV, CAPEX); a_i is the unobserved time-invariant factors affecting CFP_{it}; u_{it} is the unobserved time-varying factors affecting CFP_{it}; β_0 is the constant term; i and t stand for the firm and the time, respectively.

Using pooled OLS to estimate Equation (1) requires an assumption that the composite error term ($a_i + u_{it}$) is uncorrelated with the explanatory variables (CSP_{it} and X_{it}). This assumption holds only if the model includes all the variables simultaneously affecting CSP and CFP which is not realistic for empirical studies (Leszczensky & Wolbring, 2019). When this assumption does not hold, pooled OLS results in heterogeneity bias (also called unobserved heterogeneity) which is one of the sources of endogeneity problem (Wooldridge, 2012).

Equation (1) can also be estimated by random or fixed effects estimators. The main distinction between random and fixed effects estimators is the assumption regarding the correlation of a_i with explanatory variables. While the random effects estimator assumes that a_i is uncorrelated with explanatory variables, the fixed effects estimator allows correlation between the a_i and explanatory variables. Unlike pooled OLS or random effects estimators, fixed effect estimator is free from bias due to time-invariant unobserved heterogeneity since a_i is allowed to be correlated with explanatory variables, that is, it captures all time-invariant unobserved heterogeneity.

However, endogeneity may be also due to reverse causality between CFP and CSP and the dynamic characteristic of CFP. Reverse causality remains as a factor leading to biased estimates in both random and fixed effects estimators due to their strict exogeneity assumption which requires the unobserved time-varying error term is uncorrelated with explanatory variables. The reverse causality between CFP and CSP violates this assumption, thereby lead to biased estimates in both models (Leszczensky & Wolbring, 2019).

Dynamic endogeneity, as another problem that should be taken into consideration in CSP-CFP models, means the existence of a correlation between past and present values of the dependent variable. If this is the case, a regression model without a lagged dependent variable among explanatory variables, just as Equation (1), would produce inconsistent parameter estimates when those lagged dependent variables are correlated with other explanatory variables. Due to the dynamic nature of economic relationships (Baltagi, 2005), a dynamic panel data model should be developed and estimated with appropriate estimation methods.

Dynamic Panel Data Models

Dynamic panel data models capture the temporal dependency of the dependent variable by the inclusion of a lagged dependent variable among explanatory variables. Expression of Equation (1) with a dynamic panel data model specification is as follows:

$$CFP_{it} = \sum_{l=1}^{p_0} \gamma_l \, CFP_{it-1} + \sum_{m=1}^{M} \sum_{l=0}^{p_m} \beta_1^{(m)} \, X_{it-1}^{(m)} + \sum_{s=2}^{T} T_s d_{it}^{(s)} + a_i + u_{it} \tag{2}$$

where CFP_{it} is explained by; $p0 \geq 1$ lags of CFP, $pm \geq 0$ lags of M explanatory variables $X_{it}^{(m)}$, T-1 time dummies where $d_{it}^{(s)}$ for $t = s$ and zero otherwise, random or fixed individual effects $a_{i,}$ and idiosyncratic disturbances $u_{it.}$ Equation 2 was adopted from Kiviet (2020) who formulated the model specification for GMM estimator in software programs.

The addition of lagged dependent variable among explanatory variables brings with some basic problems which cannot be solved by pooled OLS, random or fixed effects estimators. Applying pooled OLS to Equation (2) produces biased and inconsistent parameter estimates due to the fact that the lagged dependent variable (CFP_{it-n}) is correlated with a_i. Since this correlation does not disappear as the number of observations in the dataset gets larger, pooled OLS results in biased estimates (Bond, 2002). Similarly, the random effects estimator cannot solve this correlation problem. One possible way to draw out a_i from Equation (2) is using the fixed effects estimator. However, after the within-groups transformation under the fixed effects estimator, the within transformed lagged dependent variable will be still correlated within the transformed error term when T is fixed (Baltagi, 2005; Bond, 2002).

Instrumental variables (IV) and generalized method of moments (GMM) are suggested as the most efficient methods to estimate the models with lagged dependent variables among the explanatory variables, when the time dimension of panel data is short (Kripfganz, 2019). There have been several IV and GMM estimators suggested and compared with each other since the early 1980s. (Anderson & Hsiao, 1981, 1982; Arellano, 1989; Arellano & Bond, 1991; Ahn & Schmidt 1995; Arellano & Bover 1995; Blundell & Bond, 1998…).

IV estimator developed by Anderson and Hsiao (1981) produces consistent but not efficient estimates due to not utilizing all available moment conditions (Ahn & Schmidt 1995). As a more efficient method compared to the IV estimator, the GMM estimation of Arellano and Bond (1991) transforms the data by differencing, thereby called difference GMM. Differencing means subtracting the previous observation of a variable from the current one. Instead of this transformation, Arellano and Bover (1995) introduce forward orthogonal deviations which transform the data by subtracting the average of all future available observations of a variable. This method prevents data loss caused by the differencing method in unbalanced panels. Arellano and Bover (1995) / Blundell and Bond (1998) proposed system GMM which improves efficiency by introducing more instruments than the difference GMM. System GMM uses not only lagged levels as instruments for equations in first-differences but also lagged differences as instruments for equations in levels (Roodman, 2009).

System GMM requires some assumptions to produce consistent estimates. The existence of negative first-order serial correlation and the absence of second-order serial correlation in the residuals should be satisfied for a consistent system GMM estimation. Additionally, the validity of instruments depends on the absence of correlation between the instrumental variables and error term. This exogeneity assumption of the instruments can be empirically tested by the overall overidentification and the incremental overidentification tests for each subset of instruments (Kripfganz, 2019). GMM has also some moment conditions and exclusion restrictions which cannot be tested. GMM estimation of a model including some endogenous regressors requires some exclusion restrictions on the model since these endogenous regressors cannot be used as instrumental variables because of their correlation with the error term. However, the number of instrumental variables should be higher than or at least equal to the number of regressors in the model. Based on this requirement of GMM, some lagged variables cannot be kept in the model since they are used as instruments. The resulting exclusion of regressors from the model constitutes an exclusion restriction on the model which cannot be tested (Kiviet, 2020). The moment conditions based on the classification of the variables in the model are as follows (Kiviet, 2020; Kripfganz, 2019):

$$E(y_{is}\Delta\varepsilon_{it}) = 0 \textit{ for } s \leq t-2,$$

$$E(x_{is}^{m}\Delta\varepsilon_{it}) = 0 \textit{ for } s \leq t-2 \textit{ if } x_{it}^{m} \textit{ is endogenous,}$$

$$E(x_{is}^{m}\Delta\varepsilon_{it}) = 0 \textit{ for } s \leq t-1 \textit{ if } x_{it}^{m} \textit{ is predetermined,}$$

$$E(x_{is}^{m}\Delta\varepsilon_{it}) = 0 \textit{ for } \forall s \textit{ if } x_{it}^{m} \textit{ is exogenous}$$

Taking into consideration its efficiency in unbalanced panels, system GMM was used to estimate Equation (2) in this study. However, the GMM estimator should be applied rigorously because it has some challenges which may cause biased results unless handled correctly. It is not advised for panels having a long time dimension. In the cases of many instruments, the results of GMM may be biased. Since the GMM estimator is complicated, it may produce biased estimates due to the wrong use by researchers. (Roodman, 2009).

The commands used in statistical software programs to apply the GMM estimator should be clearly understood by the user to be able to find the best reliable specification. In this study, the Stata command "xtdpdgmm" was used for the GMM estimation of Equation (2). Kripfganz (2019) has introduced "xtdpdgmm" command by asserting that "xtabond2", which is another Stata command for GMM estimation, has some bugs when dummies with factor notation are included in the model and forward orthogonal deviations are used. In a recent paper, Kiviet (2020) discussed all the inaccurate aspects of "xtabond2" in detail and cited "xtdpdgmm" as a "*promising improved alternative*".

A model specification search, which was suggested by Kiviet (2020) and Kripfganz (2019), has been conducted to find the most efficient and consistent model specification for the estimation of Equation (2). The followed process of model specification search was explained through the subsection of "Results of Dynamic Panel Data Model" in depth.

Results

Descriptives

Table 4 provides mean, standard deviation (S.D.), minimum and maximum values of variables used in regression models in this study. All the financial variables were winsorized at the bottom and top 5% to mitigate the effect of outliers.

Table 4 Descriptive Statistics

	Mean	S.D.	Min	Max
TOBIN'S Q	1.66	1.05	.75	4.72
ROA	7.30	5.98	-.84	21.56
SIZE	15.58	1.63	12.85	18.97
LEV	.58	.21	.21	.93
CAPEX	9.84	11.26	.40	42.67
ESG	50.12	16.68	7.77	95.43
ENV	49.25	21.38	4.56	98.38
SOC	50.47	21.59	4.73	98.54
GOV	50.69	20.54	2.28	98.37

Notes: All financial variables (*TOBIN'S Q, ROA, SIZE, LEV*) are winsorized at 5%. Variables are defined in Table 3.

Pairwise correlations between the variables of regression models are presented in Table 5. The variables ESG, ENV, SOC, and GOV were not included in the same regression model. Except for these variables, all the correlation coefficients in Table 5 are below 80% which means that there is no multicollinearity problem in the models of this study. Calculated variance inflation factors of these variables also confirm that multicollinearity is within acceptable limits.

Table 3 Variables Definition

	Description	Source
Dependent Variables		
TOBIN'S Q	the ratio of (market capitalization + total liabilities) to total assets	Datastream
Control Variables		
ROA	return on assets	Datastream
SIZE	the logarithm of total assets	Datastream
LEV	the ratio of liabilities to assets	Datastream
CAPEX	capital expenditure % sales	Datastream
Independent Variables		
ESG	overall ESG score	Datastream
ENV	environmental pillar score	Datastream
SOC	social pillar score	Datastream
GOV	governance pillar score	Datastream

Table 5 Pairwise Correlations

Variable	TOBIN'S Q	ROA	SIZE	LEV	CAPEX	ESG	ENV	SOC	GOV
TOBIN'S Q	1								
ROA	.7037***	1							
SIZE	-.4142***	-.4255***	1						
LEV	-.3089***	-.4817***	.4790***	1					
CAPEX	-.1324***	-.0311*	.0069	-.2001***	1				
ESG	-.0141	-.0026	.1821***	.0881***	-.0439***	1			
ENV	-.0442***	-.0269	.2487***	.0751***	-.0231	.8469***	1		
SOC	.0041	.0478***	.0709***	.0611***	-.0347**	.8569***	.6633***	1	
GOV	.0088	-.0342**	.1096***	.0727***	-.0478***	.6314***	.2830***	.2883***	1

Notes: All financial variables (*TOBIN'S Q, ROA, SIZE, LEV*) are winsorized at 5% level. Variables are defined in Table 3. *, **, *** stand for significance levels of <.10, <.05, <.01, respectively.

Regression Results

Results of Static Panel Data Model

Table 6 provides the pooled OLS, random, and fixed effects estimation results of the static panel data model expressed with Equation (1). In order to choose the most consistent and efficient estimator between pooled OLS, random, and fixed effects estimators, we carried out Breusch-Pagan LM and Hausman tests, respectively. The significant p-value of the test statistic of the Breusch-Pagan LM test indicates that random individual effects are significant, and their variances are not "0" (Baltagi, 2005). This means that the estimation of Equation (1) with the pooled OLS estimator results in biased estimates. As a second step, we employed the robust Hausman test to decide between random and fixed-effects estimators. The null hypothesis under the Hausman test, which is also an assumption of random effects, is that unobserved effect a_i is not correlated with explanatory variables. The rejection of the robust Hausman test due to the significant test statistic means that the assumption of random effects estimator is violated, therefore fixed effects estimator should be preferred.

Fixed effects estimation results in Table 6 indicate that environmental, social, and overall EGS performance of the companies have a small but positive impact on the corporate financial performance which was proxied by Tobin's Q ratio. Among the control variables, ROA was also found to be positively correlated with Tobin's Q ratio. SIZE has the biggest significant effect on Tobin's Q with a negative sign. In line with these findings, the firms with higher environmental and social performances, higher profitability, and smaller size can be said to have a higher market value.

However, for the fixed effects estimator to be consistent, the explanatory variables should be strictly exogenous. The exogeneity of the explanatory variables in Equation (1) was tested by the Wooldridge test for strict exogeneity. This test is based on the comparison of the models below:

$$CFP_{it} = \beta_0 + \beta_1 CSP_{it} + \beta_2 X_{it} + a_i + u_{it} \tag{1}$$

$$CFP_{it} = \beta_0 + \beta_1 CSP_{it} + \beta_2 X_{it} + \beta_1 CSP_{i(t+1)} + \beta_2 X_{i(t+1)} + a_i + u_{it} \tag{3}$$

The first model is the standard model which was estimated by fixed effects. In addition to the variables in the first model, the second model also includes the future values of all explanatory variables. The main idea behind the Wooldridge test for strict exogeneity is to test whether the future values in the second model are significant or not.

Table 6 Pooled OLS & Random Effects & Fixed Effects Estimation Results of Static Model – Equation 1

	Pooled OLS				RE				FE			
ROA	.102*** (.003)	.102*** (.003)	.103*** (.003)	.102*** (.003)	.058*** (.004)	.058*** (.004)	.058*** (.004)	.058*** (.004)	.045*** (.004)	.045*** (.004)	.045*** (.004)	.046*** (.004)
SIZE	-.052*** (.009)	-.054*** (.009)	-.052*** (.009)	-.054*** (.009)	-.147*** (.023)	-.147*** (.022)	-.145*** (.022)	-.146*** (.022)	-.233*** (.049)	-.235*** (.048)	-.229*** (.048)	-.223*** (.047)
LEV	.334*** (.073)	.330*** (.074)	.348*** (.074)	.328*** (.073)	.113 (.143)	.116 (.143)	.113 (.143)	.112 (.143)	.276 (.178)	.285 (.178)	.268 (.178)	.258 (.177)
CAPEX	-.000 (.001)	.000 (.001)	-.000 (.001)	.000 (.001)	.001 (.002)	.001 (.002)	.001 (.002)	.001 (.002)	.002 (.002)	.002 (.002)	.002 (.002)	.002 (.002)
ESG	**-.000** **(.001)**				**.000** **(.001)**				**.003**** **(.001)**			
ENV		**.000** **(.001)**				**.000** **(.001)**				**.002**** **(.001)**		
SOC			**-.001**** **(.001)**				**.000** **(.001)**				**.002*** **(.001)**	
GOV				**.000** **(.001)**				**.000** **(.001)**				**.001** **(.001)**
Constant	2.342*** (.184)	2.344*** (.181)	2.375*** (.185)	2.326*** (.183)	4.357*** (.379)	4.370*** (.380)	4.357*** (.378)	4.351*** (.377)	4.798*** (.720)	4.874*** (.725)	4.785*** (.724)	4.736*** (.713)
YEAR	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
IND	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

	Pooled OLS				RE				FE			
N	3,687	3,687	3,687	3,687	3,687	3,687	3,687	3,687	3,687	3,687	3,687	3,687
R2	.626	.626	.626	.626	.578	.578	.578	.578	.401	.400	.400	.406
B&P LM					.000	.000	.000					
R.Hausman									.000	.000	.000	.000

Notes: OLS, RE, and FE represent ordinary least squares, random effects, and fixed effects estimators, respectively. Standard errors which are robust to heteroscedasticity and autocorrelation are in parenthesis. All models include time (YEAR) and industry (IND) dummy variables. N denotes the number of observations. R2: square of overall correlation. B&P LM is the p-value of the test statistic of the Breusch-Pagan LM test for random effects. R. Hausman is the p-value of the test statistic of the Cluster-Robust Hausman Test. Variables are defined in Table 3. *, **, *** stand for significance levels of <.10, <.05, <.01, respectively.

After estimating the two models by fixed effect estimators and robust standard errors, the F test for joint significance of future values of explanatory variables resulted in a significant F statistic (56.99, $p<0.01$). This means that the future values of explanatory variables are correlated with the error term, thereby violates the strict exogeneity assumption of fixed effects. Therefore, we can argue that the parameter estimates in Table 6 are inconsistent and biased.

Results of Dynamic Panel Data Model

Kiviet (2020) and Kripfganz (2019) suggested a model specification search as the first step to obtaining consistent, efficient, and accurate parameter estimates as the result of the GMM estimator. After including all relevant regressors to the model based on the economic theory, the model specification process requires the classification of regressors as endogenous, predetermined, or exogeneous. A variable is strictly exogenous if it is uncorrelated with the time-varying error term at all leads and lags. On the contrary, endogenous variables are correlated with the time-varying error term at all leads and lags. Finally, predetermined variables are uncorrelated with present and future values of time-varying error term but potentially correlated with historical values (Arellano, 2003).

This study tries to follow the steps of the "sequential model selection process" of Kripfganz (2019) who adapted it from Kiviet (2019) with some revisions. Kiviet (2020) suggested treating all unlagged explanatory variables as endogenous unless proven otherwise. The first step of the model selection process is specifying an initial candidate "maintained statistical model (MSM)" including all relevant explanatory variables with sufficient lags. This initial MSM with collapsed and/or curtailed instruments for forward orthogonal deviations transformation, should include time dummies and assume all regressors as endogenous. The second step tells to estimate the initial MSM by two-step GMM estimator with Windmeijer standard errors robust to finite-sample bias.

Following the instructions in the first and second steps, an initial candidate MSM based on Equation (2) was developed. This initial model included 3 lags for all variables assuming all the unlagged regressors as endogenous. In order to prevent the biases caused by too many instruments, this initial model included the collapse option which is one of the approaches to reduce the number of instruments. Finally, since the forward orthogonal deviations (FOD) transformation minimizes data loss in unbalanced panels, the initial candidate MSM was specified as a FOD-transformed model (Kripfganz, 2019). Then two-step GMM estimator with Windmeijer standard errors robust to finite-sample bias was used to estimate this initial candidate MSM. The two-step GMM estimator is more efficient than the one-step GMM estimator when the time-varying error term is heteroskedastic and Windmeijer-corrected standard errors are used to correct the finite-sample bias of two-step standard errors.

After developing this initial candidate MSM, 28 more candidates were developed by; a) removing lagged variables with the highest p-value, b) treating explanatory variables that were classified as endogenous in the initial model as predetermined one by one, and c) adding industry dummies. The consistency of all these candidate models was checked by the specification tests used after the GMM estimation. More precisely, the Arellano-Bond test was used to check the autocorrelation of the first-differenced residuals. The existence of negative first-order serial correlation and the absence of second-order serial correlation was confirmed for all the candidate models. To test the overall validity of instruments, the Hansen overidentification test was utilized and finally, the incremental overidentification test was carried out to check the validity of each subset of instruments. Specification test results were satisfactory for all candidate models. As suggested by Kripfganz (2019), the model and moment selection criteria (MMSC) of Andrews and Lu (2001) was utilized to decide the most efficient one among the candidate models. The models with the lowest values of Akaike (AIC), Bayesian (BIC), and Hannan-Quinn (HQIC) criteria were selected and reported in Table 7.

The model specification with the lowest values of MMSC-AIC, MMSC-BIC, and MMSC-HQIC criteria was the one including TOBIN'S Q variables lagged by one, two, and three periods, and also time and industry dummies. This model treated the variables SIZE, LEV, and CAPEX as predetermined, but ROA as endogenous. It should be noted that the models treating ROA as predetermined could not pass the specification tests. This model was estimated by the two-step system GMM estimators with collapsed instruments and Windmeijer standard errors robust to finite-sample bias for the FOD-transformed model. Table 7 provides the parameter estimates of this model specification with overall ESG, ENV, SOC, and GOV as the main interest of variables, respectively.

The fixed effects results in Table 6 and system GMM results in Table 7 differ considerably with regards to the relationship between CSP and CFP. More precisely, whereas fixed effect results reveal that environmental, social, and overall EGS performance have a significant positive effect on the CFP, two-step system GMM results reveal the opposite, i.e. a significant negative impact. The insignificant relationship between governance performance and CFP is valid in both fixed effects and system GMM estimations. When it comes to control variables, whereas SIZE has a negative and significant coefficient estimate in fixed-effects results, the coefficient estimate of SIZE is not significant for all the models estimated with system GMM. Additionally, based on the fixed effects results it is possible to say that there is not a significant relationship between CAPEX and TOBIN'S Q. However, according to system GMM results, CAPEX has a significant negative effect on TOBIN'S Q except for the SOC model.

The negative causal effect of CSP on CFP can be explained by the trade-off hypothesis of Preston and O'Bannon (1997). The trade-off hypothesis, which is based on Friedman's (1970) argument indicating that "*the social responsibility of business is to increase its profits",* claims that social responsibility activities such as environmental protection, charity work consume company resources in a way that is not for the best interest of investors. Accordingly, the companies which are bearing financial costs due to their social responsibility activities fall into a disadvantaged position in comparison to their counterparts which use less or no resources for these types of activities. Ultimately, higher levels of CSP can lead to lower levels of financial performance. It is highly probable that this hypothesis is valid for a sample of developing countries as analyzed in this study since it is not an unexpected case that awareness of social responsibility activities in developing countries is less than that of developed countries.

As seen in Table 7, the first lag of TOBIN'S Q has the biggest coefficient estimate which means that the current value of TOBIN'S Q is highly dependent on the lagged value of it. Omitting this variable will result in biased parameter estimates for the other variables in the regression model. Equation (1), as a static model, does not incorporate this temporal dependency of TOBIN'S Q, thereby produces biased and inconsistent parameter estimates even it is estimated with the fixed effects estimator.

In order to verify the robustness of the system GMM results reported in Table 7, financial firms were excluded from the sample, and Equation (2) was re-estimated. The coefficient estimates of the main interest variables (ESG, ENV, SOC, GOV) were quantitatively similar to the reported parameter estimates in Table 7.

GMM results reported in Table 7 are based on a lower number of observations (1,966) than the original number of observations (3,687) in the sample because of the lagged dependent variables in the dynamic model. In order to see if the different results between FE and GMM are purely based on the omission of the dynamic terms in FE, FE results for the GMM subset of observations were also provided in the Appendix. When the results reported in the Appendix are compared with the GMM results in Table 7, it is seen that while FE estimations of the models result in positive and insignificant coefficients for ESG, ENV, and SOC variables, GMM estimation produces negative and significant coefficients for the same variables. Accordingly, we can conclude that the different results between FE and GMM are not based on the lower number of observations in GMM estimation but the omission of the dynamic terms in FE.

Table 7 Two-Step System GMM Estimation Results of Dynamic Model – Equation 2

	ESG MODEL	ENV MODEL	SOC MODEL	GOV MODEL
L1.TOBIN'S Q	.762*** (.087)	.745*** (.089)	.742*** (.087)	.756*** (.084)
L2.TOBIN'S Q	-.067 (.054)	-.055 (.055)	-.081 (.057)	-.048 (.053)
L3.TOBIN'S Q	-.048 (.040)	-.046 (.039)	-.044 (.040)	-.063 (.040)
ROA	.011 (.008)	.010 (.007)	.014* (.007)	.011 (.007)
SIZE	.019 (.028)	.021 (.030)	-.006 (.025)	.001 (.026)
LEV	-.009 (.381)	.081 (.331)	.185 (.374)	-.051 (.348)
CAPEX	-.006* (.003)	-.006* (.003)	-.006 (.004)	-.008** (.004)
ESG	**-.006***** **(.002)**			
ENV		**-.003**** **(.001)**		
SOC			**-.003**** **(.002)**	
GOV				**-.002** **(.001)**
Constant	.853 (.532)	.647 (.560)	1.080** (.520)	.845 (.519)
YEAR	YES	YES	YES	YES
IND	YES	YES	YES	YES
N	1,966	1,966	1,966	1,966
AR2	.812	.8382	.716	.997
Hansen	.621	.5593	.477	.386
Inc. Hansen (p values)	all>.10	all>.10	all>.10	all>.10

Notes: This table represents the parameter estimates of the two-step GMM estimation of Equation (2) with time (YEAR) and industry (IND) dummies, collapsed instruments, and Windmeijer-corrected standard errors for the FOD-transformed model treating all the unlagged explanatory variables as predetermined except ROA which is assumed to be endogenous. L1 & L2 & L3. TOBIN'S Q stand for TOBIN'S Q variables lagged by one, two, and three periods, respectively. Windmeijer-corrected standard errors are presented in parenthesis. N denotes the number of observations. AR2 is the p value of the test statistic of the Arellano-Bond test for second-order serial correlation. Hansen is the p value of the test statistic of the Hansen overidentification test. Inc. Hansen represents the p values of test statistics of incremental overidentification tests. Variables are defined in Table 3. *, **, *** stand for significance levels of <.10, <.05, <.01, respectively.

Conclusion

Using a sample including 3,687 observations of listed firms in BRICS countries for the period 2009-2018, this study examined the impact of CSP on CFP utilizing both static and dynamic panel data models and also various estimators including pooled OLS, random & fixed effects, and system GMM. The main motivation behind the empirical analyses of this study was to expose the inconsistent results between the static and dynamic panel data models. It was also aimed to draw attention to the challenges of the two-step system GMM which may result in biased parameter estimates unless taken into account properly.

The results of static and dynamic panel data specifications and estimations differ considerably on the main conclusion regarding the effect of CSP on CFP. Whereas the static model specification estimated with fixed effects indicates a positive and significant relationship between CSP (except for governance performance) and CFP, the results of dynamic panel data specification estimated by system GMM suggests the opposite. More precisely, there is a negative and significant relationship between CSP (except for governance performance) and CFP according to the dynamic panel data analyses. This inconsistency between the results of static and dynamic panel data analyses mainly stems from the fact that static panel data models miss the temporal dependency of the dependent variable. Accordingly, dynamic endogeneity remains a problem and result in biased parameter estimates under static panel data specifications.

The findings of this research should prompt the researchers to test the robustness of the results of static panel data analyses as it reveals the insufficiency of static panel data models while examining the nexus between CSP and CFP. However, this study also wants to draw attention to the challenges of system GMM as a dynamic panel data estimation method. System GMM is suggested as a more efficient estimator under dynamic endogeneity, however, researchers should apply system GMM rigorously to handle its challenges properly. Otherwise, system GMM may lead to wrong inferences just as static panel data methods.

This study has also some crucial findings for the authorities of capital markets and listed companies in BRICS countries. The finding indicating a negative impact of CSP on CFP should prompt capital markets to develop policies to increase the market value of corporate social responsibility activities of companies by raising awareness of the listed companies and their investors on the significance of sustainable development.

The limitations of this study may open the way to new ideas for further research. This study utilized only a market-based performance measure, further research should consider also accounting-based performance measures as a proxy for CFP. Governance indicators such as board composition, board size can be included in the models to mitigate the effect of omitted variable bias on the results.

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Appendix

	ESG MODEL	ENV MODEL	SOC MODEL	GOV MODEL
ROA	0.041*** (0.005)	0.041*** (0.005)	0.041*** (0.005)	0.041*** (0.005)
SIZE	-0.218*** (0.061)	-0.225*** (0.061)	-0.219*** (0.061)	-0.213*** (0.059)
LEV	0.264 (0.209)	0.273 (0.209)	0.263 (0.207)	0.261 (0.207)
CAPEX	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
ESG	**0.001** **(0.001)**			
ENV		**0.001** **(0.001)**		
SOC			**0.001** **(0.001)**	
GOV				**-0.001** **(0.001)**
Constant	4.546*** (0.912)	4.630*** (0.918)	4.558*** (0.912)	4.568*** (0.900)
YEAR	YES	YES	YES	YES
IND	YES	YES	YES	YES
N	1,966	1,966	1,966	1,966
R2	0.388	0.386	0.387	0.381

Notes: This table represents the parameter estimates of fixed effect estimation of Equation (1) for GMM set of observations. Standard errors which are robust to heteroscedasticity and autocorrelation are in parenthesis. All models include time (YEAR) and industry (IND) dummy variables. N denotes for the number of observations. R2: square of overall correlation. * p<0.10, ** p<0.05, *** p<0.01.

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