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Accounting for endogeneity and the dynamics of corporate social – Corporate financial performance relationship

Béchir Ben Lahouel [a,*], Brahim Gaies [b], Younes Ben Zaied [c], Abderrahmane Jahmane [a]

[a] IPAG Business School, Department of Strategy & Management, IPAG Chair "Towards an Inclusive Company", Paris, France
[b] IPAG Business School, Department of Finance, Paris, France
[c] ISTEC Business School, Paris, France

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A B S T R A C T

This paper examines the endogeneity problem in studies dealing with corporate social performance and financial performance relationship. Since randomized controlled experiments in the "Business-Research" field are often unfeasible, researchers rely mostly on observational data to make claims about "doing good – doing well" arguments. In response to several strong calls for additional well-crafted empirical research that address endogeneity, we revisit the CSP – CFP relationship, in the airline industry, to understand how endogeneity arises and how to control for it in studies based on observational panel data. We exploit various approaches such as OLS, fixed-effects, fixed-effects IV/2SLS, dynamic system GMM, and GLS estimators. We show the appropriateness behind the use of the dynamic system GMM estimator and its benefits over the fixed-effects estimator. In addition, we demonstrate that results in models that do not account for endogeneity lead to inflated estimations, misleading interpretations and wrong theoretical propositions about the dynamic nature of CSP-CFP relationship.

1. Introduction

This study responds to the multiple calls from Social Issues in Management (SIM) researchers to overcome the modeling misspecification that have tarnished previous empirical studies about the causal relationship between Corporate Social Performance (CSP) and Corporate Financial Performance (CFP). This study examines how CSP would affect CFP when panel data observations are used by shedding light on the endogenous and the dynamic nature of this relationship. Hence, following Wintoki et al. (2012), this study accounts for heterogeneity, simultaneity, and dynamic endogeneity that have been considered as the main sources of endogeneity biases, but have been missing in prior empirical literature since then.

The revelation of a business case for corporate social responsibility (CSR) through the search for a positive relationship between corporate social performance and corporate financial performance has dominated the empirical research during the last 40 years (Wood, 2010). Notwithstanding, a rich and wide theoretical literature regarding different relationships between CSP and CFP, Rost and Ehrmann (2017) point out the lack of consensus with respect to its empirical validity. More importantly, the signs of the relationship reported are sometimes positive, negative or non-significant from time to time (Igalens and Gond, 2005; McWilliams and Siegel, 2000; Orlitzky, 2008). Although, the results of several meta-analysis tend to confirm slightly the existence of a positive relationship (Albertini, 2013; Dixon-Fowler et al., 2013; Endrikat et al., 2014; Margolis et al., 2009; Margolis and Walsh, 2001, 2003; Orlitzky et al., 2003; Orlitzky and Swanson, 2008; Rost and Ehrmann, 2017), the results of recent empirical studies remain very mixed and heterogeneous. These conflicting and opposable results, which often show a low statistical significance, intensify, yet again, the point of discord and the paradox surrounding the CSP-CFP relationship, amongst organizational researchers.

Recent studies have begun to question the scientific validity of previous research on CSP – CFP relationship since many researchers (e.g., Endrikat et al., 2014; Garcia-Castro et al., 2010; Schreck, 2011) have displayed conceptual, theoretical and methodological problems. Other researchers believe that these noticeable discrepancies are due to the weakness of econometric models used, the sample selection bias, the time horizon mobilized, the organizational environment, and the shortcomings in measuring

* Corresponding author.
E-mail addresses: b.benlahouel@ipag.fr (B. Ben Lahouel), b.gaies@ipag.fr (B. Gaies), ybzaied@gmail.com (Y. Ben Zaied), a.jahmane@ipag.fr (A. Jahmane).

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CSP and CFP variables (Margolis and Walsh, 2003; McWilliams and Siegel, 2000; Orlitzky, 2011; Wood and Jones, 1995).

As mentioned above, most of prior studies have concentrated on uncovering the business case for CSP, through examining the CSP – CFP relationship, to support managers in setting up strategies for assessing the financial outcomes of their CSR initiatives. This study is different. As such, less concern is granted to revive the theoretical debate on the relationship between CSP and CFP and more interest is bestowed to *what* makes the results so ambiguous. This study focuses mainly on the persistent and recurrent issue that has not been treated meticulously in prior research: the failure to account for endogeneity bias. Indeed, CSP-CFP research is plagued with endogeneity issues (Bénabou and Tirole, 2010) particularly when researchers attempt to explain causality between the two variables relying on observational panel data. Additionally, this paper spells out the dynamic endogeneity issue that has been overlooked within traditional econometric models (e.g., Ordinary Least Squares (OLS), fixed-effects and random-effects estimators). These models lead to both inflated and biased estimations when they are used across "static" panel data, which inherently disregard the connection between past and present financial performance. By referring to Wintoki et al. (2012), the entire history of present financial performance has to be explained by lagged financial performance, as we cannot exclude any feedback from past shocks on the current value of the dependent variable. Thus, financial performance is driven by dynamics whose effects remain permanent and display significant temporal correlations.

According to Shahzad and Sharfmann (2017) and Crane et al. (2017), the main factor responsible for the ambiguity of findings, stemming from previous CSP – CFP research, is endogeneity. Jean, Deng, Kim & Yuan (2016) underline the major issue, induced by endogeneity, in SIM studies mobilizing regression analysis in order to extract causal inferences. Specifically, causal inferences, standing for empirical results of hypothetical associations between endogenous and exogenous variables, may be infected by endogeneity bias, and consequently may distort the direction and the amplitude of the relationship between variables (Ketokivi and McIntoch, 2017), and misrepresent results interpretation as well as theoretical and managerial implications (Zaefarian et al., 2017).

Although the methods for its resolution were available for several decades, endogeneity bias represented a "*blind spot*" (Zaefarian et al., 2017: 40) in empirical SIM studies. What is more, the number of research published in high ranked management journals (at least 66% and up to 90%) has not adequately addressed the endogeneity bias (Antonakis et al., 2014; Hamilton and Nickerson, 2003).

Very recently, Yang and Baasandorj (2017, hereinafter Y&B) analyzed CSP – CFP relationship of international air carriers using fixed-effects model of panel data covering the period from 2006 to 2015. Their findings were heterogeneous depending on whether CFP was evaluated by accounting-based (ROA) or market-based measures (Tobin's Q). In this study, we revisit the CSP – CFP relationship by extending Y&B's study in three main directions:

1. *Time horizon.* We expand the period by four years and use larger sample than Y&B's one covering the period from 2004 to 2017. Hence, our sample seems to be more representative of the international airline industry
2. *Modeling.* We explore several econometric extensions over Y&B's model. First, Y&B (2017) employed a standard estimator that is the fixed-effects model for panel data. We hypothesize that this estimator is biased and is unable to exploit the dynamic nature, of the relationship between CSP and CFP, in a panel data. Second, Y&B treat CSP as an exogenous variable. However, management' decisions to engage in CSP are presumably endogenous, which means that engaging strategies in favor of firm's stakeholders is not random but rely on the firm's expected performance outcomes. In that respect, we address the potentially endogeneity issue by (a) exploiting the dynamic nature of the panel and (b) using the two-step system dynamic panel GMM model.
3. *Replication.* In a last step, we consider the same sample as used by Y&B (2017) and utilize first the fixed-effects model, then the system dynamic panel GMM estimator. The rationale behind this approach is to make the case that the obtained results differ from an estimator to another and that it is critical to use the adequate estimator in studies relying on observational panel data.

We employ the same measures of variables than those of Y&B (2017) and use both identical and different procedures for model estimation. In this way, we have set two broad purposes in this paper: (1) show the importance of econometric rigor to understand the quality of the relationship between CSP and CFP, and (2) apply the dynamic GMM estimator to deal with endogeneity issues and compare the results to those obtained from traditional fixed-effects estimator.

Interestingly, contrary to Y&B (2017) s' results, we find that CSP does not affect accounting-based measure of CFP after controlling for endogeneity. Nevertheless, when we use the fixed-effects estimator, we roughly find the same results as those of Y&B. Our findings are consistent with those of previous research (e.g., Garcia-Castro et al., 2010; Schreck, 2011) which illustrate that the positive relationship between CSP and CFP may disappear when introducing contemporaneous estimators that control for endogeneity. More important, our results prove the need to conduct research with a threshold econometric rigor (e.g., testing and correcting for heteroskedasticity and serial correlation). In general, failure to statistically correct for the aforementioned issues (e.g., endogeneity, heteroskedasticity and serial correlation), can lead to faulty theoretical conclusions as well as wrong managerial recommendations.

The rest of this paper is structured as follows. We briefly present the background of the study in the next section. Then, we present the endogeneity bias and the study methodology before describing our empirical models and presenting our findings. The last section contains the conclusion, academic implications for future research and limitations.

2. Literature review

Previous research shows a small but positive relationship between CSP and CFP. The causality between the two constructs has not been demonstrated since then and results from empirical studies remain mixed and hitherto inconclusive. The variability of these results was explained by the diversity and divergence of the theoretical frameworks mobilized. Several attempts to classify these theories have been advanced by researchers (e.g., Bénabou and Tirole, 2010, Brammer and Millington, 2008, Marom, 2006, Moore, 2001, Peloza, 2006, Preston and O'bannon, 1997, Orlitzky, 2011, Schuler and Cording, 2006, Rost and Ehrmann, 2017, Wang et al., 2015, etc.) depending on whether the relationship is linear or not.

2.1. Linearity assumption

This assumption allows the CSP-CFP relationship to describe the causal sequence of the two variables and predict the signs of their interaction. Three main theoretical models are distinguished.

The first model describes a negative relationship between CSP and CFP supporting Friedman's trade-off theory, which purports that CSR activities are fundamentally subversive. This model recognizes that investments in CSR activities may hurt a firm's profitability by inhibiting optimal resource allocation (Kang et al., 2010), above all, when CSR should be considered as the responsibility of the society, not the firm. Moreover, this model supports the managerial opportunism hypothesis whereby managers' motivation to pursue CSR programs is initiated by their personal agenda, own egocentricity, and their desire to be acknowledged as philanthropists (Bénabou and Tirole, 2010; McWilliams et al., 2006). Indeed, in order to maximize their private earnings, managers may reduce CSR expenditures, when CFP is high. Similarly, when CFP is low, managers may increase CSR expenditures to counteract their underwhelming results (Makni et al., 2009). As a consequence, the pursuit of managers' self-interest (Williamson, 1975) through CSR activities, to the detriment of maximizing shareholder wealth (Friedman, 1970), is nothing but agency costs (Jensen and Meckling, 1976) that prejudice CFP. Some researchers (e.g., Allouche and Laroche, 2005; Gond, 2001; Salzmann et al., 2005) have also assumed the existence of a negative synergy between the two constructs forming a vicious circle that mutually and simultaneously destroys both financial and social value.

The second model, which asserts that CSR activities are an important diver for improving financial performance, is based on the social impact theory (Cornell and Shapiro, 1987) rooted from Freeman's stakeholder theory (1984). This perspective reflects the "Business Case for CSR" where the long-term synergy between the CSP and CFP is established through the company's ability to acquire resources and mold internal capabilities that create competitive advantage (Barney, 1991). Also, this perspective suggests that meeting the needs of different stakeholders leads to the development of a goodwill reservoir (Bhattacharya and Sen, 2004) acting as a hedge instrument against reputational risk during crises (Schnietz and Epstein, 2005; Ziglidopoulos, 2001) as well as an insurance tool covering financial returns through a heightened firm's reputation (Orlitzky and Benjamin, 2001; Peloza, 2006). Waddock and Graves (1997) found that CSP is positively associated with prior and subsequent CFP. Hence, according to the slack resources theory, better CFP potentially raises the availability of slacks and may allow firms to invest more in socially responsible domains and put CSR activities into action. Additionally, Waddock and Graves (1997) argued for a positive synergy between CSP and CFP. Based on the social impact theory and the slack resources theory, they have put forward the simultaneous positive relationship between CSP and CFP, forming a virtuous circle.

The third model suggests no particular, unilateral or reverse directional, relationship between CSP and CFP because the costs and benefits of being socially responsible tend to cancel each other out (McWilliams et al., 1999). Other scholars (e.g., Aupperle et al., 1985; McWilliams and Siegel, 2000; Orlitzky, 2001) have argued that CSP – CFP relationship may be disrupted by many confounding variables "*that have been shown to be important determinants of profitability*" (McWilliams and Siegel, 2000, p. 603). Actually, the proponent of this line of reasoning argue that CSP – CFP relationship hardly exists because it is powered by many organizational factors (e.g., R&D expenses, advertising expenditures, etc.) as well as non-discretionary factors beyond the managers' control (e.g., labor market conditions, environmental and social regulations stringency, etc.) (Germann et al., 2015; Guiral, 2012; Goll and Rasheed, 2004).

2.2. Non-linearity assumption

Some researchers drop the linearity hypothesis and assert that the noticeable discrepancies among studies are mainly due to more complex curvilinear relationships between CSP and CFP (Brammer and Millington, 2008; Moore, 2001; Wang et al., 2016). Two models are identified as follows.

The first model describes an inverted U-shaped curve of the CSP – CFP relationship. It suggests that excessive investments in CSR activities may become a destructive force for a firm's value. This model indicates the existence of an optimal level of CSP beyond which the firm incurs direct costs and agency costs leading to a reduction in its profitability (Kurucz et al., 2008; Lankoski, 2000; Moore, 2001; Salzmann et al., 2005; Wagner et al., 2001). Wang et al. (2016) state that once stakeholders requests are satisfied, it is no longer worthwhile to invest more in CSR activities that are costly, administratively burdensome, and inducing a CFP marginal deficit.

The second model describes a U-shaped curve of the CSP – CFP relationship. According to this configuration, high level of CFP is hypothesized to be linked with either very high level or very low level of CSP. Bhattacharya and Sen (2004) conceptualize the CSP – CFP relationship by analogy to Porter's (1980) generic strategies suggesting that firms that adopt either a differentiation or a cost-leadership strategy are likely to outperform their competitors that are "stuck in the middle". Thus, a firm can develop an inherent cost advantage over rivals by improving its efficiency along the value chain when it renounces to invest in expensive CSR activities. Conversely, competitive advantage can be developed by differentiating the firm, in the eyes of prominent stakeholder groups, through the development of an offer of product and services resulting from a design approach and production process that are both recognized as socially responsible.

3. Replication

Our primary purpose in this study is to use, in a first step, the same estimation procedure (fixed-effects estimator), following Y&B (2017), to determine whether slightly different samples generate different results. In a second step, we apply the system GMM estimator for panel data in order to control for endogeneity and the dynamic relationship between current values of the independent variable on the one hand, and CSP as well as past values of CFP, as one of the dependent variables, on the other hand. Finally, we re-estimate the same sample as Y&B (2017) using first the fixed-effects model, then the system GMM estimator for panel data. The rationale behind this is to demonstrate that different econometric modeling leads to different empirical results. Hence, appropriate modeling in SIM research is needed and required in order to enhance not only the knowledge creation process but also to provide relevant construction of the social reality of the causal relationship between CSP and CFP.

Y&B explore the causal relationship between CSR activities and financial performance, via fixed-effects panel data analysis, in the international airlines industry. They find that CSR activities,[1] social performance as well as environmental performance affect positively and significantly financial performance via return on assets ratio (ROA). Conversely, financial performance, captured by Tobin's Q, cannot be improved by CSR activities and its social and

[1] Yang and Baasandorj (2017) used CSR scores from Thomson Reuters ASSET 4 Database. The overall CSR score (ESG score) is an aggregated score that contains three category scores that are rolled up into three pillar scores: Environmental, Social and Corporate Governance. In their empirical study, Yang and Baasandorj (2017) utilized the overall CSR score that they labeled 'CSR performance', the environmental score that they labeled 'environmental performance' and the social score that they labeled 'social performance'. In this study, we use the same overall CSR score, environmental score, and social score as Yang and Baasandorj (2017) did.

environmental components. Moreover, leverage shows conflicting significant impact toward CFP depending on whether the latter is expressed with accounting-based or market-based measures.

Over 10 years (2006–2015), Y&B observed 130 firms and reported mixed results about CSP – CFP relationship in discord with prior literature in the airlines industry (see Kim et al., 2014; Seo et al., 2015; Tsai and Hsu, 2008; Wang et al., 2015). We hypothesize that Y&B's empirical results might be biased by the presence of serious limitations relating to their econometric modeling.

For instance, CFP may be driven by many other interposing variables that might also correlate with CSP. Sometimes, information on these variables is absent (e.g., due to unavailable data, we cannot observe data relating to investment in R&D, advertising expenditure, etc.). Thus according to Wooldridge (2002), an endogeneity problem might rise because of omitted variable bias.

4. Endogeneity bias

Typically, empirical studies testing for the causal link between CSP and CFP are based on regression analysis made on panel data with the following modeling:

$$\boldsymbol{CFP_{it}} = \beta_0 + \beta_1\ \boldsymbol{CSP_{it}} + \beta' X_{\ it} + \varepsilon_{it} \tag{1}$$

Where CFP_{it} indicates the corporate financial performance of firm i in year t, CFP_{it} indicates the corporate social performance of firm i in year t, $X_{\ it} = (x_1, \ldots, x_k)$ represent the set of control variables, and ε_{it} represents the error term.

According to Crane et al. (2017), this simple model is tainted by endogeneity issues, which are articulated by a violation of the non-correlation hypothesis between the explanatory variables and the error term. Garcia-Castro et al. (2010) and Schreck (2011) were the first to raise and analyze the problem of endogeneity in empirical research studying CSP – CFP relationship. They argue, as highlighted by Hamilton and Nickerson (2003) in the strategic management field, that top management's decision to invest in a process of 'CSP improving' is endogenous to managers' anticipation of the financial benefits reported by such a strategic decision. Thereafter, Bénabou & Tirole (2010: 16) agree and mention, "*SBR [Social Responsible Behavior] and profitability are clearly both endogenous variables*".

Endogeneity may be due to:

1) a problem of simultaneity (or reverse causality) which occurs when CSP and CFP variables affect/cause each other and have reciprocal feedback loops (Attig et al., 2016; El Ghoul, Guedhami & Pittman, 2015; McGuire et al., 1988; Waddock and Graves, 1997);
2) unobserved heterogeneity that corresponds to the omission of variables in the regression equation. McWilliams and Siegel (2000: 603) argue that studies that have led to positive associations between CSP and CFP are doubtful "*in the sense that they omit variables that have been shown to be important determinants of profitability*".
3) inadequate measurements instruments to capture the constructs of interest. This occurs when researchers cannot perfectly measure CSP and CFP variables and therefore their true values remain unobserved (Wooldridge, 2002).

In this way, it remains essential to refine the econometric modeling, in order to improve the analysis and the grasp of causal mechanisms between CSP and CFP. Studies must henceforth use more elaborate econometric modeling that consider and correct for endogeneity. Our main purpose in this study, after showing how endogeneity bias may cause incorrect estimates in CSP – CFP relationship, is to provide a comprehensive procedure as to how the general dynamic generalized method of moments (GMM) model can be applied to produce consistent estimates when dealing with panel data.

5. Data and methodology

5.1. Sample

In our study, we aimed to replicate Y&B's sample as closely as possible. Thus, using Thomson Reuters Datastream ASSET4 ESG database, we identify 28 air carriers (12 additional firms comparing to Y&B's sample) that constitute our full panel. Following Y&B, we used unbalanced panel data with 248/209 firm-year observations within the study period from 2004 to 2017. Hence, since Y&B's study was undertaken, additional firm year have become available before 2006 and beyond 2015. In comparison, Y&B's sample comprises 130 observations (see table A in appendix).

5.2. Variables

CFP. In general, CFP can be depicted either by accounting- or market-based measures. Accounting-based measures represent firm internal organizational efficiency reflecting the way in which various managerial strategies have affected the profitability of the firm (Cochran and Wood, 1984; Endrikat et al., 2014; Orlitzky et al., 2003). Following Davidson and Worrell (1988), Carton and Hofer (2006), and Orlitzky et al. (2003), we assume that market-based measures reflect investors' expectations about future values of risk-adjusted opportunities that can be captured by a firm. Each of these measures focuses on different aspects of performance and presents its own biases (McGuire et al., 1986; Wu, 2006). While some researchers (e.g., Chakravarthy, 1986; Davidson and Worrell, 1990; Fernandez, 2002) suggest that, the exploration of the CSP – CFP relationship should be examined using market measures, other authors (e.g., McGuire et al., 1988; Orlitzky et al., 2003; Wu, 2006) find that CSP is more strongly correlated with accounting measures than market indicators. Following previous studies (Saeidi et al., 2015; Wiengarten et al., 2017; Xie et al., 2017), we choose return on assets (ROA) ratio as an accounting-based measure of financial performance. In addition, we follow the recommendation of prior CSP-CFP research (Bhandari and Javakhadze, 2017; Shahzad and Sharfman, 2017) and employ Tobin's Q, which reflects the market-based measure of CFP. Alike Y&B (2017), ROA was calculated as net income over total assets and we estimate Tobin's Q by the following formula: (Market value+Preferred stock+Long-term debt)/Total assets.

CSP. Following the Y&B (2017) approach, CSP was measured by CSR score retrieved from Thomson Reuters ASSET4 ESG. CSR score include the overall scores on CSR, environmental performance score (ENV) and social performance score (SOC).

Control variables. We closely followed the original study's methodology and we enter the same set of control variables. We include firm size (measured as the market capitalization of the firm), leverage (ratio of the total liabilities over total assets), and firm age.

5.3. Empirical models and estimation methods

In order to quantify the effect of corporate social performance on financial performance, we use the dynamic unbalanced[2] panel data model, following Bouslah, Kryzanowski & M'Zali (2018) and El

[2] For this reason, the number of observations varies slightly from one regression to another in our estimations (see Tables below).

Ghoul, Guedhami, Kim & Park (2018), by adding a lagged dependent variable among the control variables. Thus, our model can be expressed as follows:

$$CFP_{it} = \alpha_0 + \gamma CFP_{it-1} + \alpha_1\ CSP_{it} + \beta' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where CFP_{it} is ROA or TOBQ; CFP_{it1} is the one year lagged ROA or TOBQ (L.ROA and L.TOBQ); CSP_{it} represents the indicators of corporate social performance (CSR or ENV or SOC); X_{it} indicates the set of control variables (SIZE, LEV and AGE); α_0 is a constant; μ_i is the company-specific effect; λ_t is the time-specific effect; and ε_{it} is the error term.

We have chosen a dynamic panel specification because most research on the CSP-CFP relationship (e.g. Hillman and Keim, 2001; Panwar et al., 2017; Theodoulidis et al., 2017; Waddock and Graves, 1997) has used static panel models, by omitting the temporal dependency of the corporate financial performance. In fact, they assumed that there is no correlation between the "*past*" and the "*present*" values of the corporate financial performance (i.e., Cov (CFP_{it}, CFP_{it-1}) = 0)), even though this assumption is counter-intuitive. Previous literature indicates that current managerial decisions are largely defined with respect to previous levels of profitability (Garcia-Castro et al., 2010). Hence, adding a lagged financial performance variable enables as to possess the entire history of the right-hand-side of the equation, which explain the historical realizations of present financial performance (Greene, 2011; Wintoki et al., 2012). In so doing, we are able to better capture the dynamic nature of the panel and thus use the adequate statistical methodology that captures the endogenous dynamics.

In addition, according to Bond (2002), even when the estimation of the lagged dependent variable (CFP_{it-1} in our case) is not statistically significant, the dynamic specification may be crucial for recovering consistent estimates of the other variables. On the other hand, the absence of the lagged dependent variable within the set of control variables can cause the omitted variable bias, which is among the main sources of endogeneity issues (Antonakis et al., 2014; Ketokivi and McIntosh, 2017; McWilliams and Siegel, 2000).

Furthermore, the estimation of equation (1) may cause three main econometric issues which are the potential sources of endogeneity bias (e.g., simultaneity bias (D1), dynamic endogeneity (D2), and unobserved heterogeneity bias (D3)).

The first one (D1) is related to the endogeneity of the corporate social performance variables (CSR, ENV and SOC) because causality may run in both directions from these variables to the corporate financial performance variables (ROA and TOBQ) and vice versa. Therefore, CSR, ENV and SOC can be correlated with the error term (ε_{it}). That is the simultaneity bias.

The second difficulty (D2) consists of the presence of L.ROA and L.TOBQ among the explanatory variables. Indeed, these lagged variables could be correlated with the error term and lead to the serial correlation problem. That is the dynamic endogeneity bias. Moreover, business research scientists strongly argue that CSP-CFP relationship is dynamic: CSP affects CFP and is influenced by it as well (Nelling and Webb, 2009; Roberts and Dowling, 2002; Waddock and Graves, 1997). Studies dealing with the determinants of financial performance have been challenged by the presence of potential dynamic endogeneity, which means that there is a dynamic link between current values of CSP and past realizations of CFP. In this instance, Wooldridge (2002) and Roodman (2008) argue that fixed-effects estimation may be biased and lead to incorrect inferences.

The third difficulty (D3) is that the company-specific effect (μ_i), which reflects the time-invariant characteristics of each company, such as country of origin, may be correlated with the explanatory variables. That is the unobserved heterogeneity bias.

According to Wooldridge (2005) and Murtazashvili and Wooldridge (2008), D1 can be resolved[3] by using the fixed-effects instrumental variables and the two-stage least squares estimator (fixed-effects IV/2SLS). This estimator is based on the external instruments defined by the user, such as the lagged value of the endogenous interest variable (Attig et al., 2013; Benlemlih and Bitar, 2016; Cai et al., 2011; Schultz et al., 2010; Wintoki et al., 2012). However, this type of instruments, called "external" may be weak. Under this scenario, the fixed-effects (IV/2SLS) estimator may be biased (Bound et al., 1995).

Furthermore, D3 can be treated through the transformation of equation (1) in first difference, as expressed below:

$$\Delta CFP_{it} = \Delta\alpha_0 + \gamma\Delta CFP_{it-1} + \alpha_1\ \Delta CSP_{it} + \beta'\Delta X_{it} + \Delta\mu_i + \Delta\lambda_t + \Delta\varepsilon_{it} \quad (3)$$

Thus, the company-specific effect (μ_i) is controlled:

$$\Delta\alpha_0 = \Delta\mu_i = 0 \quad (4)$$

Nevertheless, this transformation (equation (2)) induces a new difficulty (D3'). It is the correlation between the error term in difference ($\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-1}$) and the dependent variable in difference lagged ($\Delta CFP_{it-1} = CFP_{it-1} - CFP_{it-2}$).

By referring to Arellano and Bond (1991), we note that the first-differenced GMM panel data estimator (GMM in difference) not only resolves D3' and D3 but also D2 and D1. Indeed, through this estimator the endogenous explanatory variables expressed in difference (ΔCFP_{it-1}) are instrumented by their lagged value.

Although, even if the GMM in difference estimator generates internal instruments[4] and resolves the endogeneity problems, it has some limitations. It reduces the number of observations and could give rise to relatively weak instruments. In consequence, to obviate these limitations, Blundell and Bond (1998) combined the instruments in difference and the instruments in level. This implies that the variables in difference are instrumented through their values in level and the variables are instrumented by their values in difference, as follows:

$$\begin{cases} CFP_{it}\alpha_0 + \gamma CFP_{it-1} + \alpha_1 CSP_{it} + \beta' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \\ \Delta CFP_{it} = \gamma\Delta CFP_{it-1} + \alpha_1\Delta CSP_{it} + \beta'\Delta X_{it} + \Delta\lambda_t + \Delta\varepsilon_{it} \end{cases} \quad (5)$$

Thus, Blundell & Bond (1998) developed the system GMM estimator. According to Roodman (2009a; 2009b), by using the Monte Carlo experiments, Blundell and Bond (1998) proved that the system GMM is more efficient and robust than GMM in difference. Also, they highlight that the two steps GMM system estimator[5] is more asymptotically efficient than the one step GMM system estimator.

Due to all of these arguments, we utilized[6] the two-step system

[3] Due to D1 and D2, the estimators which are not based on the instrumental variables technique (ordinary least squares (OLS) fixed-effects (FE), random-effects (RE), among others), are not appropriated to estimate equation (1) because they are not able to resolve the endogeneity bias (Roodman (2009a)).

[4] The GMM methods generate "internal" instruments, which are more robust than "external" instruments used in the fixed-effects (IV/2SLS) model, (Roodman (2009a; 2009b)).

[5] The first step estimation assumes the absence of serial correlations and heteroskedasticity of the error term. In a second step, the vector of the residuals calculated from the first step is used to develop a convergent variance-covariance matrix of the error term. At this second stage, the hypothesis of the absence of serial correlations and heteroskedasticity of the error term is confirmed (Roodman, 2009a).

[6] By referring to Roodman (2009a; 2009b), we added the corrections by Newey and Windmeijer (2009), to optimize the number of instruments and prevent the problem of instrument proliferation. Also, we fixed the heteroskedasticity problem, according to White's (1980) method.

Table 1
Summary statistics.

Variable	Mean	Std.Dev.	Min	Max
ROA	3730	5281	−22,990	24,170
TOBQ	0,803	0313	0,350	2251
SIZE	15,275	1054	11,673	17,519
LEV	0,740	0175	0,401	1424
AGE	3796	0,564	2303	4575
CSR	4034	0,222	3219	4394
ENV	4032	0,345	2373	4565
SOC	4071	0,343	2598	4545

Data from 2004 to 2017, including the 28 air carriers in the sample.

GMM to estimate our model expressed above in equation (1).

Lastly, according to Roodman (2009a; 2009b), the validity of the two-step system GMM estimator depends on the quality of the instrumental variables (Hansen-test), as well as the absence of second-order serial correlations of the error term (AR2).[7]

6. Results

6.1. Descriptive statistics, correlations and control variables

Table 1 shows the descriptive statistics related to the variables used in our model including 28 air carriers observed from 2004 to 2017. These statistics converge in mean and in standard deviation with the statistics displayed by Yang and Baasandorj (2017). However, our sample is relatively more representative of the international airline industry, since Yang and Baasandorj (2017) only studied 16 companies from 2006 to 2015.

Table 2 represents the correlation matrix of the variables used in our model (equation (1)). It reveals that the corporate social performance variables are not correlated with ROA, except ENV that has a negative correlation with the latter. Conversely, there is a negative correlation between TOBQ and the corporate social performance variables, except SOC which is not correlated with TOBQ. LEV and AGE are negatively correlated with ROA and TOBQ, which in turn are positively correlated with SIZE. Also, the lagged dependent variables (L.ROA and L.TOBQ) are positively and significantly correlated with their values in level (ROA and TOBQ). This corroborates our choice to use a dynamic panel specification expressed through equation (1).

Table 3 provides us with a first intuition (before the baseline estimations) regarding the coefficient of the control variables. It shows the negative coefficients of LEV and AGE, and the positive coefficients of SIZE, L.ROA and L.TOBQ. Indeed, to obtain these results, we estimated equation (1) through the ordinary least squares estimator (OLS), by omitting the lagged dependent variables (L.ROA and L.TOBQ) at first and then, by adding them.

When we add L.ROA and L.TOBQ (regressions (2) and (4) in Table 3), the adjusted R-squared (R2adj) increases significantly, in comparison with the regressions (1) and (3) in Table 3, which are related to the estimations of equation (1), where L.ROA and L.TOBQ have been excluded. This is evidence that the dynamic specification is more explanatory of corporate financial performance than the static specification.

6.2. Baseline estimations

Table 5 shows the basic regressions for our model expressed in equation (1), using the two-step system GMM estimator. It highlights three main results.

Firstly, the positive and significant signs of the coefficients of the lagged dependent variables (L.ROA and L.TOBQ) indicate the correlation between “past” the “present” values of corporate financial performance (Cov (CFP_{it}, CFP_{it-1}) $\neq$ 0)). This is consistent with our choice to use a dynamic panel specification in the present study. Secondly, there is significant positive influence of SIZE on both ROA and TOBQ, and a negative influence of AGE on TOBQ. Thirdly, the non-significance of the coefficients of CSR, ENV and SOC shows that these corporate social performance indicators do not affect the corporate financial performance measured by ROA and TOBQ.

In order to compare these results with those of Yang and Baasandorj (2017), we re-estimated equation (1), excluding the lagged dependent variables (L.ROA and L.TOBQ), using the fixed-effects estimator, as the Y&B did in their analysis. The outputs of Table 4 indicate the results of these estimations. They emphasize that CSR has a significant positive effect on ROA. Also, ENV positively and significantly influences ROA and TOBQ. Thus, these findings are in contradiction with the results drawn from Table 5. This discrepancy can be explained by four main ways.

First, bearing in mind, as we proved above, that the dynamic model is more appropriate in examining CSP-CFP relationship, the divergence may occur, because in Table 5, we used the dynamic panel model and in Table 4, like Yang and Baasandorj (2017), we made use of a static panel model. The low value of R^2adj in Table 4 consolidated this conclusion.

Second, due to the endogeneity of the corporate social performance variables, estimators, which are not based on the instrumental variables technique, such as the fixed-effects estimator, are not suitable. They may be biased, according to Arellano and Bond (1991), Blundell and Bond (1998) and Roodman (2009a).

Third, the P-value of Wald test drawn in Table 4 reveals that the null hypothesis of the homoskedasticity of the error term is strongly rejected (Long and Ervin, 2000). Consequently, Y&B's fixed-effects estimations most likely suffer from the heteroskedasticity problem. Under this scenario, the standard inferences become invalid and the use of a new estimator namely the generalized least squares (GLS) estimator is required (Reed and Ye, 2011; Juhl and Sosa-Escudero, 2014). In the same vein, we should point out that Yang and Baasandorj (2017) have not tested the homoskedasticity of the error term in their article and not corrected for the heteroskedasticity problem.

Lastly, when looking at Table 4, the Wooldridge test P-value highlights that the null hypothesis of no serial correlation is strongly rejected (Drukker, 2003). This biases the standard errors and causes the results to be less efficient, according to Baltagi and Li (1995). Similarly, Reed & Ye (2011) recommend the use of the GLS estimator. Furthermore, it is important to underline that Yang and Baasandorj (2017) considered the classical Durbin Watson test to study the serial correlation in their paper. However, this test is not appropriate for panel data, with reference to Born and Breitung (2016).

6.3. Replication of the Yang and Baasandorj (2017) study

To highlight, once again, that the results of Yang and Baasandorj (2017) suffer from several fundamental econometric weaknesses, we have adopted the same estimates as made by the authors considering their sample, namely 16 air carriers observed between 2006 and 2015. As shown in Table 6, by mimicking the approach followed by Yang and Baasandorj (2017), we re-estimated equation

[7] In all our two-step system GMM estimations, the P-value of the Hansen test is higher than 10% level. This indicates that the null hypothesis of the absence of high correlation between the instrumental variables and the error term is verified. Therefore, the instrumental variables used seem to be valid and the two-step system GMM estimator is convergent. This result is consolidated by the acceptance of the null hypothesis of the absence of serial correlation of the error term in order two, as is shown by the P-values (P-value *AR2*) of the Arellano and Bond (1991) test, which are above the threshold of 10% in all our regressions.

Table 2
Correlation coefficients.

	ROA	TOBQ	L.ROA	L.TOBQ	SIZE	LEV	AGE	CSR	ENV	SOC
ROA	1.0000									
(p-values)										
TOBQ	0.4424	1.0000								
(p-values)	(0.0000)									
L.ROA	0.4656	0.4125	1.0000							
(p-values)	(0.0000)	(0.0000)								
L.TOBQ	0.3954	0.7759	0.4420	1.0000						
(p-values)	(0.0000)	(0.0000)	(0.0000)							
SIZE	0.4339	0.3272	0.3442	0.2530	1.0000					
(p-values)	(0.0000)	(0.0000)	(0.0000)	(0.0002)						
LEV	−0.4021	−0.3272	−0.4034	−0.3462	−0.3682	1.0000				
(p-values)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)					
AGE	−0.1750	−0.3626	−0.1825	−0.3781	0.0376	0.3315	1.0000			
(p-values)	(0.0057)	(0.0000)	(0.0066)	(0.0000)	(0.5552)	(0.0000)				
CSR	−0.0425	−0.1753	−0.0899	−0.2093	0.0370	0.1021	0.3521	1.0000		
(p-values)	(0.5054)	(0.0070)	(0.1842)	(0.0024)	(0.5613)	(0.1081)	(0.0000)			
ENV	−0.1258	−0.2975	−0.1519	−0.3500	0.0042	0.1465	0.3240	0.7292	1.0000	
(p-values)	(0.0478)	(0.0000)	(0.0242)	(0.0000)	(0.9473)	(0.0207)	(0.0000)	(0.0000)		
SOC	−0.0523	−0.1036	−0.0889	−0.1099	0.0198	0.1480	0.3122	0.7541	0.5719	1.0000
(p-values)	(0.4125)	(0.1126)	(0.1891)	(0.1132)	(0.7554)	(0.0195)	(0.0000)	(0.0000)	(0.0000)	

This table reports the correlation coefficients of Pearson between the variables used in this paper.

Table 3
Control variable selection.

	Dependent: ROA		Dependent: TOBQ	
	(1)	(2)	(3)	(4)
L.ROA		**0.256*****		
		(0.054)		
L.TOBQ				**0.700*****
				(0.091)
SIZE	1.768***	1.661***	0.095***	0.043***
	(0.341)	(0.279)	(0.018)	(0.014)
LEV	−7.147***	−1.773	−0.249**	0.004
	(2.611)	(1.794)	(0.111)	(0.072)
AGE	−1.046*	−0.976*	−0.190***	−0.075**
	(0.596)	(0.508)	(0.032)	(0.029)
Constant	−14.035**	−17.531***	0.244	−0.139
	(5.512)	(4.714)	(0.303)	(0.244)
Observations	248	219	236	209
R2	0.267	0.360	0.270	0.630
R2adj	0.258	0.348	0.261	0.622
Fisher-statistic	22.46	30.14	27.53	43.89

Estimations: OLS robust correction.
Standard errors are presented below the corresponding coefficient.
Symbols *, ** and *** mean significant at 10%, 5% and at 1%.

(1), excluding the lagged dependent variables (L. ROA and L. TOBQ) and based on the fixed effects model. In doing so, we achieve about the same results as Y&B. Indeed, CSR seems to have a positive and significant influence on ROA. In addition, ENV has a significant and positive effect on ROA.

In addition, when the regressions applied to the same spatio-temporal framework are executed but using the system dynamic panel GMM estimator instead of the fixed-effects model, while adding the lagged dependent variables (L.ROA and L. TOBQ) these effects disappear. Indeed, as shown in Table 7, neither CSR nor ENV have a significant impact on ROA. Again, this discrepancy can be explained by: i) the endogeneity problem (see the discussion in section 4); ii) the heteroskedasticity problem (see P-value of the Wald test in Table 6); and iii) the serial correlation problem (see P-value of the Wooldridge test in Table 6).

Overall, this comparative analysis shows that the results differ from one estimator to another and that it is therefore essential to use the appropriate estimator in studies based on panel observation data in the CSP-CFP relationship.

6.4. Robustness tests

In order to verify the robustness of our baseline estimations illustrated in Table 5, we re-estimated equation (1), excluding the lagged dependent variables (L.ROA and L.TOBQ) and using two alternative methods, namely the fixed-effects GLS estimator and the fixed-effects IV/2SLS estimator.

The first estimator (see Table 8, regression 1 to 6) fixed the heteroskedasticity and the serial correlation problems (Reed and Ye, 2011) related to the outputs of the fixed-effects regressions reported in Table 4. The main findings, in Table 8 (regression 1 to 6), show that there is no significant effect of corporate social performance indicators (CSR, ENV and SOC) on neither ROA nor TOBQ. In addition, the X2-statistic confirms the overall significance of the model, while the R-squared reveals the model's relatively weak explanatory power compared to the dynamic panel specification.

On the other hand, the results of the fixed-effects IV/2SLS estimator drawn from Table 8 (regression 7 to 12) highlight that CSR, ENV and SOC have no significant impact on ROA and TOBQ, knowing that this model controls the endogeneity bias. In addition, the X2-statistic testifies to the overall significance of the model and the P-value of Sargan/Hansen test justifies the validity of the instrument (Wooldridge, 2005; Murtazashvili and Wooldridge, 2008). Following Attig et al. (2013), Benlemlih and Bitar (2016), Samet and Jarboui (2017), and the recommendations of Wintoki et al. (2012), we employ a two-period lagged CSP variable as an instrument for the fixed-effects IV/2SLS estimator to extract the exogenous characteristics of CSP. Hence, we need an IV that is highly correlated with CSP but uncorrelated with residual error term (El Ghoul et al., 2018).

In sum, the two alternative estimators (fixed-effects GLS and fixed-effects IV/2SLS) prove the robustness of our baseline estimations based on the two steps GMM system estimator. Therefore, it seems that when we fixed the heteroskedasticity and serial correlation problems and controlled the endogeneity bias, the coefficients of CSR, ENV and SOC lose their significance. This result evidences the absence of a significant impact of corporate social performance on financial performance in the airline industry.

7. Discussion

In contrast to Y&B's finding, our results suggest that CSP

Table 4
CSP – CFP: Fixed-effects regressions.

	Dependent: ROA			Dependent: TOBQ		
SIZE	3.133***	3.097***	3.083***	0.247***	0.247***	0.243***
	(0.557)	(0.547)	(0.561)	(0.029)	(0.029)	(0.029)
LEV	−14.362***	−15.013***	−14.755***	0.396*	0.382*	0.363*
	(4.822)	(4.733)	(4.851)	(0.216)	(0.213)	(0.216)
AGE	−0.642	−2.090	1.457	−0.130	−0.188	−0.026
	(3.474)	(3.319)	(3.252)	(0.158)	(0.153)	(0.147)
CSR	**3.110***			**0.088**		
	(1.870)			(0.084)		
ENV		**4.461*****			**0.141****	
		(1.422)			(0.065)	
SOC			**0.682**			**−0.043**
			(1.271)			(0.057)
Constant	−43.637***	−42.536***	−40.766***	−3.141***	−3.115***	−2.915***
	(12.937)	(12.509)	(13.048)	(0.597)	(0.582)	(0.601)
Observations	248	248	248	236	236	236
R2	0.332	0.353	0.325	0.306	0.318	0.304
R2adj	0.236	0.260	0.228	0.204	0.218	0.202
Fisher-statistic	26.87	29.49	25.96	22.56	23.85	22.37
Wald test (P-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Wooldridge test (P-value)	0.0000	0.0000	0.0000	0.0079	0.0156	0.0068

Estimations: Fixed-effects model. Time and fixed effects are included in all the regressions.
Standard errors are presented below the corresponding coefficient.
Symbols *, ** and *** mean significant at 10%, 5% and at 1%.

Table 5
CSP – CFP: System GMM regressions.

	Dependent: ROA			Dependent: TOBQ		
L.TOBQ				0.389**	0.433***	0.420***
				(0.147)	(0.102)	(0.116)
L.ROA	0.404**	0.406**	0.330*			
	(0.174)	(0.195)	(0.168)			
SIZE	2.080***	1.986***	2.507***	0.171***	0.158**	0.168**
	(0.556)	(0.666)	(0.507)	(0.058)	(0.064)	(0.067)
LEV	−4.504	−6.576	−5.908	0.276	0.338	0.499
	(7.994)	(6.156)	(6.554)	(0.362)	(0.366)	(0.490)
AGE	−1.295	−0.791	−1.204	−0.183**	−0.204***	−0.191**
	(0.965)	(1.059)	(0.940)	(0.075)	(0.065)	(0.088)
CSR	**−0.158**			**0.021**		
	(2.445)			(0.149)		
ENV		**−1.487**			**0.097**	
		(1.718)			(0.095)	
SOC			**0.048**			**−0.008**
			(1.560)			(0.153)
Constant	−20.753	−14.035	−27.244**	−1.738*	−1.852	−1.710
	(13.280)	(8.467)	(10.159)	(0.980)	(1.238)	(1.027)
Observations	219	219	219	209	209	209
AR2 (P-value)	0.932	0.921	0.920	0.866	0.864	0.877
Hansen (P-value)	0.608	0.387	0.541	0.371	0.362	0.449

Estimations: Two-step system GMM with Windmeijer (2005) small sample robust correction.
Time and fixed effects are included in all the regressions.
Standard errors are presented below the corresponding coefficient.
Symbols *, ** and *** mean significant at 10%, 5% and at 1%.

variables (measured by Thomson Reuters Datastream ASSET4 ESG scores) do not affect firm financial performance. Additionally, our results are contradictory with those from prior studies and key meta-analysis that show a small but positive relationship between CSP and CFP (Berman et al., 1999; Margolis et al., 2007; Orlitzky et al., 2003; Waddock and Graves, 1997; Zhao and Murrell, 2016). We would argue that endogeneity bias might enlighten the results of earlier studies. Thus, our results are consistent with those of Garcia-Castro et al. (2010) that show when empirical modeling controls for endogeneity issues, the positive (negative) CSP-CFP relationship fades away. We also argue with prior research (Hamilton and Nickerson, 2003; Margolis and Walsh, 2003; Shaver, 1998) which stipulates that failure to account for the endogenous decision of the firm to engage in CSP, lead to sample-selection bias. According to Shahzad and Sharfman (2017), this bias (similar to an omitted variable bias) is ubiquitous in CSP-CFP research since business research scientists select samples of only those firms that are integrated in extra-financial rating agencies (e.g., KLD, SAM, VIGEO, DATASTREAM, etc.).

In our study, we pointed out the convenience of employing a dynamic framework when investigating CSP-CFP relationship. Then, we show the appropriateness behind the use of the GMM estimator and its benefits over the fixed-effects estimator (it assumes that current observations of CFP are completely independent

Table 6
CSP – CFP: Fixed-effects regressions.

	Dependent: ROA			Dependent: TOBQ		
SIZE	2.864***	2.670***	2.683***	0.319***	0.320***	0.308***
	(0.892)	(0.872)	(0.901)	(0.048)	(0.047)	(0.047)
LEV	−20.616**	−21.870**	−22.169**	0.446	0.477	0.350
	(8.869)	(8.705)	(8.989)	(0.387)	(0.378)	(0.382)
AGE	−1.798	−1.316	3.011	0.341	0.199	0.501**
	(6.483)	(6.013)	(5.941)	(0.282)	(0.260)	(0.252)
CSR	**6.131***			**0.030**		
	(3.391)			(0.148)		
ENV		**5.402****			**0.159**	
		(2.412)			(0.104)	
SOC			**1.501**			**−0.128**
			(2.164)			(0.091)
Constant	−43.736*	−38.572*	−39.071*	−5.809***	−5.839***	−5.524***
	(22.939)	(22.402)	(23.225)	(1.025)	(0.999)	(1.016)
Observations	125	125	125	119	119	119
R2	0.374	0.384	0.357	0.410	0.423	0.421
R2adj	0.261	0.272	0.241	0.296	0.312	0.310
Fisher-statistic	15.67	16.35	14.59	17.17	18.14	17.98
Wald test (P-value)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Wooldridge test (P-value)	0.0234	0.0225	0.0126	0.0025	0.0081	0.0054

Estimations: Fixed-effects model. Time and fixed effects are included in all regressions.
Standard errors are presented below the corresponding coefficient.
Symbols *, ** and *** mean significant at 10%, 5% and at 1%.

Table 7
CSP – CFP: System GMM regressions.

	Dependent: ROA			Dependent: TOBQ		
L.TOBQ				**0.487*****	**0.475*****	**0.528*****
				(0.098)	(0.136)	(0.087)
L.ROA	**0.112**	**0.053**	**0.291**			
	(0.355)	(0.595)	(0.436)			
SIZE	5.285**	5.615***	7.073***	0.142	0.167	0.189
	(1.823)	(1.513)	(1.165)	(0.152)	(0.131)	(0.128)
LEV	−0.329	0.182	20.538	0.500	0.819	1.166
	(17.355)	(12.238)	(21.984)	(0.864)	(1.275)	(1.064)
AGE	−3.198	−2.150	−4.179	−0.179	−0.238	−0.184
	(2.561)	(6.832)	(4.030)	(0.400)	(0.315)	(0.232)
CSR	**−2.092**			**0.072**		
	(20.042)			(0.313)		
ENV		**−5.016**			**0.052**	
		(13.719)			(0.209)	
SOC			**−5.229**			**0.022**
			(5.045)			(0.067)
Constant	−58.641	−56.049**	−85.447***	−1.784	−2.087	−2.803
	(42.336)	(22.143)	(25.855)	(1.585)	(2.052)	(2.239)
Observations	109	109	109	103	103	103
AR2 (P-value)	0.548	0.536	0.850	0.312	0.330	0.315
Hansen (P-value)	0.330	0.313	0.258	0.619	0.712	0.713

Estimations: Two-step system GMM with Windmeijer (2005) small sample robust correction.
Time and fixed effects are included in all regressions.
Standard errors are presented below the corresponding coefficient.
Symbols *, ** and *** mean significant at 10%, 5% and at 1%.

of past values of CFP) which, has been shown to be biased when exploring a dynamic link between CSP and CFP. In this way, we proved that empirical inconsistencies might arise due to the non-consideration of the dynamic framework.

Actually, in order to overcome the drawbacks relating to the use of "static" models in previous studies (e.g., Inoue and Lee, 2011; Lee et al., 2013a, b; Theodoulidis et al., 2017; Yang and Baasandorj, 2017), we recommend the use of "dynamic" model that should be written: CFP $= f$ (past CFP, CSP, control variables, fixed-effects). Consequently, our key findings are described below:

First, when we apply the OLS estimator to Y&B's "static" model, by introducing lagged financial variable and excluding CSP variables, we find an improvement in the statistical significance (adjusted R-squared) of the model. The R^2 rises from 26.7% to 36% when ROA is the dependent variable and from 27% to 63% when Tobin's Q is the dependent variable. This result illustrates the usefulness of a dynamic framework in our study.

Second, when we apply the fixed-effects estimator to Y&B's "static" model, we overall find the same results as those of Y&B (2017): CSP components affect positively and significantly ROA but no significant relationship is detected with Tobin's Q (except for environmental performance). Moreover, our results reveal that Y&B's fixed-effects model is facing two big issues in regression analysis using panel data: heteroskedasticity and serial correlation

Table 8
CSP – CFP: Fixed-effects GLS and IV/2SLS regressions.

	Fixed-effects GLS regressions						Fixed-effects IV/2SLS regressions					
	Dependent: ROA			Dependent: TOBQ			Dependent: ROA			Dependent: TOBQ		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SIZE	1.661***	1.674***	1.656***	0.117***	0.116***	0.117***	2.331***	2.431***	2.239***	0.282***	0.287***	0.344***
	(0.488)	(0.487)	(0.488)	(0.020)	(0.020)	(0.020)	(0.630)	(0.588)	(0.618)	(0.037)	(0.036)	(0.054)
LEV	−10.809***	−10.657***	−10.968***	−0.135	−0.141	−0.133	−15.275**	−14.682***	−16.316***	0.355	0.409	0.132
	(3.628)	(3.607)	(3.636)	(0.132)	(0.130)	(0.132)	(5.937)	(5.267)	(5.693)	(0.301)	(0.265)	(0.390)
AGE	−0.966	−0.719	−0.903	−0.187***	−0.180***	−0.186***	6.510	−0.405	7.644	0.335	−0.141	0.638
	(0.890)	(0.846)	(0.872)	(0.053)	(0.052)	(0.054)	(7.070)	(6.687)	(4.936)	(0.356)	(0.339)	(0.423)
CSR	**1.573**			**−0.010**			**−1.315**			**−0.061**		
	(1.819)			(0.079)			(5.915)			(0.294)		
ENV		**−0.227**			**−0.042**			**4.636**			**0.332**	
		(1.205)			(0.060)			(4.494)			(0.220)	
SOC			**0.930**			**−0.014**			**−2.809**			**−0.225**
			(1.141)			(0.048)			(3.412)			(0.259)
Constant	−16.274	−10.262	−13.754	−0.141	−0.015	−0.135	−40.309**	−40.009**	−36.273**	−4.837***	−4.740***	−6.158***
	(10.425)	(9.633)	(9.101)	(0.486)	(0.423)	(0.406)	(17.222)	(15.766)	(17.252)	(0.882)	(0.832)	(1.593)
Observations	248	248	248	236	236	236	192	192	192	184	184	113
R2	0.211	0.210	0.211	0.356	0.355	0.356	0.308	0.320	0.302	0.353	0.354	0.452
X2-statistic	52.84	56.24	53.13	61.36	62.62	62.06	291.1	297.1	288.9	3700	3708	2322
Sargan/Hansen (P-value)							0.9718	0.4563	0.5243	0.4905	0.8061	0.6440

Estimations: Fixed-effects Gefneralized least squares model (GLS) and fixed-effects instrumental variables and two-stage least squares (IV/2SLS) model.
Time and fixed effects are included in all the regressions.
Standard errors are presented below the corresponding coefficient.
Symbols *, ** and *** mean significant at 10%, 5% and at 1%.

(see P-value of respectively Wald Test and Wooldridge test in Table 4). Consequently, we re-estimate the same "static" model (see below) with the adequate estimator namely GLS estimator as recommended by Baltagi (2005).

Third, when we apply the GMM estimator, after accounting for endogeneity issues, we find no significant link between CSP and CFP. These findings are fundamental in our paper and are conflicting with prior research. The results of superior management of the relationship with stakeholders are not directly and systematically related to greater (lower) financial profitability. Thus, the quality of the relationship between CSP and CFP is very sensitive to the appropriateness of the employed empirical models and estimators.

Fourth, regardless of which model is employed, the estimated results show that the relation between past and current financial performances is statistically significant (positive). This result is in line with prior studies (Van Vu, Tran, Van Nguyen & Lim, 2018; Wintoki et al., 2012) which stated that ignoring this relationship in empirical models lead to failure in capturing the real impacts of CSP on CFP.

As a final step, we checked the robustness of our results derived from the GMM estimator by posing two scenarios. First, in order to prove that Y&B's "static" model suffers from heteroskedasticity and serial correlation problems, we re-estimate it with the fixed-effects GLS estimator. The stemming results show the absence of relationship between CSP and CFP. These findings converge with those resulting from the GMM estimator. Second, to control for endogeneity bias, we introduce the fixed-effects IV/2SLS estimator in order to correct for that bias and estimate Y&B's "static" model. Once again, the related results are not surprising and confirm those found in the GMM estimator.

8. Conclusion

The main purpose of this paper was to re-examine the causal effect of CSP on CF in the airline industry, taking as a reference the study of Yang and Baasandorj (2017). In order to exploit the dynamic nature between CSP and CFP, we assume that CSP-CFP relationship should be explored using dynamic panel data, because modeling phenomena as complex as corporate social performance implications require employing sophisticated set of empirical modeling.

Overall, our study supports, to some extents, the neutral relationship between CSP and CFP. Similar to McWilliams and Siegel (2000), we show that when the model is properly specified,[8] by controlling, *inter alia*, for endogeneity and specially omitted variables, prior estimates are biased and there is a neutral effect of CSP on CFP. Conversely, inconsistent estimators with several econometric biases, the problem of endogeneity, the problem of heteroscedasticity and the problem of serial correlation, can lead to inflated results, misleading interpretations and misleading theoretical proposals and managerial recommendations on the CFP-PFP relationship. Indeed, we contend that there are so many confounding micro and macro factors between CSP and CFP that a causal link barely exists.

8.1. Academic implications for future research

Our article presents only a replication of the work of Yang and Baasandorj (2017). Our intent is not to generalize our findings regarding CSP-CFP relationship. Our goal is to show that, so far, methodological practices regarding causal modeling in our field of research is still unsatisfactory. Our findings are consistent with prior recent research in CSP-CFP literature (e.g., Bénabou and Tirole, 2010; Crane et al., 2017; Garcia-Catro et al., 2010; Shahzad and Sharfman, 2017) regarding endogeneity problems. In this article, we look to raise the awareness of SIM scholars to the problem of endogeneity in studies based on panel data observation. We have

[8] McWilliams and Siegel (2000) incorporated R&D expenditures in their model and showed that the relationship between CSP and CFP is neutral.

proved that endogeneity, coupled with additional statistical problems (e.g., heteskedasticity and serial correlation), has skewed prior empirical models, and thus has led to inconsistent estimates and faulty inferences. We methodologically make the case how to tackle endogeneity issues in panel data by studying respectively the differences in findings reported under various approaches such as OLS, fixed-effects, GMM, and GLS estimators. We demonstrate that results in models that do not account for endogeneity lead to inflated estimations, misleading interpretations and wrong theoretical propositions about CSP-CFP relationship.

Today, methodological advances are available for SIM scholars to incorporate reliable measurement and valid analysis. Many solutions are available to researchers contrarily to several decades ago and, consequently, it is no longer reasonable to model CSP − CFP relationship relying only on OLS estimator and even fixed-effects estimator without instrumental variable(s).

Finally, our aim in this paper is that dealing with endogeneity bias should become the rule of thumb for causal relationships in SIM studies.

8.2. Limitations

Although we believe that we explored a promising ground within this study, we recognize its helpfulness but also its limitations, which may provide fertile field for further research and contributions. First, sample size and observations number were small due to our willingness to replicate the work of Yang and Baasandorj (2017). The study was focused only on the airline industry. Hence, our results are not only non-extendable to other industries but also not generalizable for other CSP-CFP studies. Second, as we mentioned previously, CSP-CFP studies suffer from sample-selection issues. Since we cannot use randomized experiments, our sample contains only airline carriers whose CSP scores were available at Datastream database. Finally, in order to replicate as close as possible Yang and Baasandorj (2017)'s study we introduce only three control variables. However, "business research" scholars have used a plethora of control variables that can be added, in future studies, to the right-hand-side of the regression equation.

Appendix 1

Table A
firms in the sample.

Company	Country	Years of data
Air Asia Group Bhd	Malaysia	2010–2016
Air Canada	Canada	2010–2016
Air China Ltd	China	2010–2016
Air France KLM	France	2004–2017
Air New Zealand	New Zealand	2015–2017
American Airlines	U.S.A.	2008–2016
Cathay Pacific	Hong kong	2004–2016
China Airlines	Taiwan	2010–2016
China Southern	China	2010–2016
Delta Air	U.S.A	2008–2016
Deutsche Lufthansa	Germany	2004–2016
Easyjet PLC	UK	2004–2017
Eva Airways	Taiwan	2010–2016
Japan Airlines	Japan	2013–2017
JetBlue Airways	U.S.A	2015–2016
Korean Air Lines Co Ltd	South Korea	2010–2016
LATAM Airlines	Chile	2009–2016
Qantas Airways Ltd	Australia	2004–2017
Ryanair	Ireland	2005–2017
SAS AB	Sweden	2004–2017
Singapore Airlines	Singapore	2005–2017
SkyWest	U.S.A	2015–2017
Southwest Airlines	U.S.A	2004–2016
Thai Airway	Thailand	2011–2017
Turkish airlines	Turkey	2010–2016
United Continental	U.S.A	2008–2016
Virgin A	Australia	2009–2016
WestJet	Canada	2008–2016

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