# Investment Inefficiency and Corporate Social Responsibility

Journal of Productivity Analysis (2022) 58:95–108
https://doi.org/10.1007/s11123-022-00641-4

# Investment Inefficiency and Corporate Social Responsibility

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Accepted: 13 June 2022 / Published online: 27 June 2022


**Abstract**

We demonstrate how earlier approaches to model the impact that corporate social responsibility (CSR) has on investment inefficiency are likely to be incorrect and propose use of the stochastic frontier methodology to model this relationship. We apply the approach to a sample of European listed companies, providing robust evidence that CSR performance is negatively associated with investment inefficiency. This result is consistent with the claim that high CSR firms are characterized by low information asymmetry and high stakeholder solidarity, which may represent a source of competitive advantage, helping to decrease investment inefficiency.

**Keywords** Corporate social responsibility · Stochastic frontier model · Partly linear model

## 1 Introduction

In a world without frictions, firms can reach optimal investment levels, carrying out all positive net present value projects and forgoing all negative net present value projects (Modigliani & Miller, 1958). However, both the theoretical and empirical literature shows that there exist frictions that lead firms to deviate from their optimal levels of investment, commonly known as investment inefficiency. The prior literature suggests that one of the main sources of friction that leads to investment inefficiency is information asymmetry (Myers & Majluf, 1984). Information asymmetry between managers and shareholders can affect the cost of raising funds and project selection when they have private information. Uninformed investors may demand a return premium to invest in firms where they have an information disadvantage suggesting that information asymmetry raises firms' cost of capital to raise external funds. This in turn leads to under-investment.

Understanding the determinants of information asymmetries is thus of great importance to firm managers. One key determinant that has received a great deal of attention is corporate social responsibility (CSR), which defines a set of corporate practices that improve the social and environmental standards of the markets in which companies operate. CSR shifts corporate goals from value maximization for shareholders towards broader satisfaction for multiple stakeholders (Paul & Siegel, 2006). The rise in firms' interest of adopting CSR is a result of the growing pressure from various stakeholder groups on firms to consider the social and environmental consequences of their operations and to provide more transparency and openness with respect to their actions (Molina-Azorín, Claver-Cortés, López-Gamero & Tarí, 2009).

The benefits of CSR have been widely studied with evidence finding that CSR contributes to business value through revenue generation (Belu & Manescu, 2013, McWilliams & Siegel, 2001), cost control (Roberts & Dowling, 2002), risk management (Choi & Wang, 2009), improved information quality (Cho, Lee & Pfeiffer Jr, 2013, Lopatta, Buchholz & Kaspereit, 2016), productivity change (Kapelko et al., 2021), technical efficiency (Becchetti & Trovato, 2011, Forgione, Laguir & Staglianò, 2020) and

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investment inefficiency (Benlemlih & Bitar, 2018). This last stream is especially salient to our work here. Finally, Awaysheh, Heron, Perry & Wilson (2020, pg. 2) note that "Despite evidence that CSR is increasingly considered to be important by firms and capital market participants, there remains an unsettled debate among researchers regarding the relation between CSR and firm performance." Our work speaks to this debate through investment inefficiency.

It is common in the investigation of the impact of CSR on investment inefficiency to use a set of firm characteristics in a two step fashion. This two step approach begins by constructing estimates of firm investment inefficiency, usually through a first stage regression which models firm investment based on past sales growth, and then regresses the residuals (taken to be investment inefficiency) on firm characteristics. Recent studies that use this two step approach to investigate CSR and the distribution of investment inefficiency include Benlemlih & Bitar (2018), Samet & Jarboui (2017) and Zhong & Gao (2017). However, this approach attributes **all** deviations from optimal investment levels to investment inefficiency and does not allow for noise, omitted variables which determine the optimal level of investment, nor misspecification of the relationship between past sales and current investment levels. These omissions most likely produce biased parameter estimates in the second stage regression. Moreover, this two-stage approach treats both positive and negative residuals in the same fashion. However, investment inefficiency is likely to work in a purely one-sided fashion, lowering optimal investment levels as financial frictions prevent firms from borrowing to invest in future project streams. Due to the fact that noise is not accounted for, this too will lead to biased estimates of the impact of determinants of investment inefficiency (Wang, 2003). These biased estimates, potentially including that associated with CSR, then have the potential to lead to misguided insights.

As we will detail later, investment inefficiency acts as a strictly one-sided force on optimum investment levels, with additional variation in firm level investment being driven by stochastic shocks. These two disturbances then appear together and lead to overall variation in investment levels. It is important to adequately separate these effects to rigorously decipher the impact that CSR (or any other potential determinant) has on investment inefficiency. This two-stage approach has been shown to be illogical and inconsistent in Wang & Schmidt (2002), Schmidt (2011), Parmeter & Kumbhakar (2014) and Parmeter, Wang & Kumbhakar (2017) when applied to a composed error term.

Given this coupling of stochastic noise and pure investment inefficiency, the preferred approach is to explicitly account for the presence of investment inefficiency in the first stage investment model and to directly recover the influences of firm level characteristics. This can readily be accomplished in the stochastic frontier setting (Chen, Delmas & Lieberman, 2015, Lieberman & Dhawan, 2005). Such an approach, however, typically requires specifying stringent and untestable distributional assumptions on the makeup of the composed error, which may not pass empirical scrutiny. Here we elect to go in another direction and estimate the stochastic frontier model using partly linear methods (Parmeter, Wang & Kumbhakar, 2017, Tran & Tsionas, 2009). This approach will allow us to eschew potentially controversial distributional assumptions, determine the optimum level of firm investment and assess the impact of various determinants on investment inefficiency, including CSR.

Using data on an unbalanced panel of European listed companies between 2009 to 2016, we provide new evidence that enriches the debate on the value of high CSR involvement. Our results reveal that the estimated coefficient of CSR is negative and economically and statistically significant, a finding consistent across the array of various stochastic frontier specifications we consider. For comparison we also estimate the two stage model proposed by Benlemlih & Bitar (2018), where we first estimate investment inefficiency as the residual from a prespecified model of investment and then run a separate regression of the investment inefficiency on the hypothesized determinants. Again, this two-stage model ignores the composed error structure of the investment model and is likely to lead to biased parameter estimates if any of the determinants also influence pure investment levels.

Our findings here show that the two stage model results in estimates of the effects of the explanatory variables on investment inefficiency which are well below those from the single stage approach we advocate for here. Specifically, ignoring investment inefficiency from the outset leads the two stage method to *understate* the importance of CSR when explaining the association between CSR and investment inefficiency. This finding is consistent with the argument in Wang & Schmidt (2002) that ignoring the dependency of inefficiency and the determinants in the first stage would lead to under dispersed inefficiency estimates and the coefficients of the second stage are likely to be biased downward. Moreover, our primary model produces estimates of CSR that suggest much stronger effects on investment levels.

We note that the data used here has recently been deployed in several other studies interested in aspects of CSR (Engida, Rao & Oude Lansink, 2020, Kapelko et al., 2021). Engida, Rao & Oude Lansink (2020) deployed data envelopment analysis to estimate distance functions within a dynamic by-production framework that specifies a technology set integrated with CSR. This model offers a useful framework to benchmark firm performance, accounting for resources diverted from the production of desirable outputs (conventional outputs) to socially responsible outputs as well as the mitigation effects of socially responsible output. The framework captures the trade-offs between different types of outputs and helps provide a more accurate representation of the production process when evaluating performance. Kapelko et al. (2021) examined the association between productivity change and CSR. In Kapelko et al. (2021), they also deployed data envelopment analysis to estimate directional distance functions to study the drivers of productivity change. So, while we are using the same data as earlier work, the focus here is much different. Our focus is on the impact of CSR on firm level inefficiency and to point out that earlier attempts to do this have done so in a manner inconsistent with what the efficiency literature as studied in exacting detail. We also deploy stochastic frontier analysis and this offers a different estimation approach than these earlier papers as well. This study makes an important contribution to the debate on whether involvement in CSR is value-increasing by demonstrating that higher CSR performance is associated with lower investment inefficiency.

The remainder of this paper is organized as follows. Section 2 reviews the literature on investment inefficiency and CSR. Section 3 presents the stochastic frontier method and the empirical issues that are likely to arise with the two-stage approaches which currently dominate the literature. Section 4 describes our data while Section 5 reports the empirical results. Section 6 concludes the paper.

## 2 Investment Inefficiency and CSR Performance

### 2.1 Investment Inefficiency

The literature on investment has been dominated by the Q-theory and accelerator theory. The Q-theory of investment proposes that investment opportunities could be summarized by the ratio of the market value of capital stock to its replacement cost (Fazzari, Hubbard, Petersen, Blinder & Poterba, 1988, Gertler & Gilchrist, 1994, Hayashi, 1985, Tobin, 1969). Hayashi (1982) extends the Q-theory to models of investment claiming that average Q can sufficiently capture investment opportunities and explain investment demand under the assumption of perfect competition, constant returns and convex costs of adjusting the capital stock with capital as the only quasi-fixed factor.

According to accelerator theory, fluctuations in sales or output motivate changes in investment. In other words, the accelerator model links the demand for capital goods to the level or change in a firm's output or sales (Abel & Blanchard, 1986, Fazzari, Hubbard, Petersen, Blinder & Poterba, 1988). Although the Q investment demand model has many attractive features, other approaches such as accelerator models have displayed better empirical performance (Abel & Blanchard, 1986).

In the absence of capital market imperfections and financial constraints, Tobin's $Q$ and current and past sales are sufficient to characterize optimal investment decisions of the firm. However, both theoretical and empirical evidence indicates that there exists frictions that lead to observed investment levels being less than the efficient (optimal) investment level (Bhaumik, Das & Kumbhakar, 2012, Parmeter, Wang & Kumbhakar, 2017, Wang, 2003). These frictions are commonly attributed to investment inefficiency.

### 2.2 CSR and Investment Inefficiency

CSR reflects the commitment of firms to behave responsibly by honoring ethical values and respect people, communities, and the natural environment (White, 2006). Understanding the effect of CSR involvement on investment inefficiency is important because it is critical to a firm's growth. High CSR firms may be associated with low investment inefficiency due to low information asymmetry and better management practices due to stakeholders' consideration (stakeholder theory). A number of studies have shown that high CSR firms are associated with low information asymmetries (Cho, Lee & Pfeiffer Jr, 2013, Dhaliwal, Li, Tsang & Yang, 2011). According to Cho, Lee & Pfeiffer Jr (2013) and Dhaliwal, Li, Tsang & Yang (2011) high CSR firms consider the social and environmental consequences of their operations and disclose more information with respect to their actions compared to low CSR firms. Consequently, high CSR firms are likely to be associated with lower investment inefficiency due to the presence of fewer information asymmetries. If a firm addresses information problems and lowers information asymmetries, its potential for investment would be less constrained. This is due to the fact that investors demand a lower cost of capital to a firm whose stock contains fewer information asymmetries.

Another way to view this relationship is through stakeholder theory. Stakeholder theory considers CSR engagement as a mechanism to develop and maintain firm reputation (Cornell & Shapiro, 1987, Cui, Jo & Na, 2018, Dhaliwal, Li, Tsang & Yang, 2011, Dhaliwal, Radhakrishnan, Tsang & Yang, 2012, Freeman, 2010). Meeting stakeholders' expectations helps to improve firm reputation, which in turn increases its financial performance. This is more likely due to low investment inefficiency. More formally, our main hypothesis is that corporate social responsibility performance is negatively related with investment inefficiency.

## 3 Methods

### 3.1 Existing Approaches

The common strategy for estimating investment inefficiency and incorporating determinants into the analysis is first to estimate deviations from expected optimal investment, which is reflected in the residuals of the investment model, and then to run a regression of these residuals on the hypothesized determinants; Benlemlih & Bitar (2018), Zhong & Gao (2017), Cook, Romi, Sanchez & Sanchez (2019), Li & Liao (2014), Chen, Hope, Li & Wang (2011) and Biddle et al. (2009) all implement this two stage approach.

The first step suffers from omitted variable bias unless the investment frontier is correctly specified and all deviations around optimal investment represent investment inefficiency. Ignoring the dependence of investment inefficiency on potential determinants will lead to the estimated first-step efficiency index to be under-dispersed, and the coefficients of the second-step regression are likely to be biased downward even when the determinants of investment and firm level characteristics are uncorrelated (Wang & Schmidt, 2002).

To see this more explicitly, consider the simple setting of predicting optimal investment with lagged sales growth, as in Chen, Hope, Li & Wang (2011) and Biddle et al. (2009):

$$Inv_{it} = \beta_0 + \beta_1 \Delta Sales_{it-1} + \varepsilon_{it}, \tag{1}$$

where $Inv_{it}$ is firm $i$'s investment in period $t$, $\Delta Sales_{it-1}$ is lagged sales growth for firm $i$ and $\varepsilon_{it}$ captures all other deviations from optimal investment in period $t$. This regression is commonly estimated for each sector-year for which there exists a minimum number of observations and is routinely presented without $t$ subscripts.

Estimation of equation (1) captures the investment frontier and $\widehat{\varepsilon}_i$ represents variation around optimal investment. It is this metric which is termed investment inefficiency and further regressed on a set of determinants, including CSR:

$$\widehat{\varepsilon}_i = \alpha_0 + \alpha_1 CSR_i + OtherFactors = \alpha Z_i + \nu_{it}, \tag{2}$$

where $Z_i$ is the vector of determinants used to capture investment inefficiency including CSR and $\nu_i$ is a stochastic shock which picks up any omitted variation in $\widehat{\varepsilon}_i$.

The two main issues with this approach, as highlighted earlier, are that if any of the determinants of investment inefficiency influence actual investment levels directly, then (1) is misspecified and this will lead to omitted variable bias. Secondly, even if we were to assume that (1) was correctly specified, treating $\varepsilon_i$ as investment inefficiency ignores stochastic noise and measurement error, which implies that the true level of variation in investment inefficiency is not adequately captured in (2), leading to further biases in the estimates of $\alpha$.

The approach which we propose is to treat shocks to optimal investment as two separate components which make up the error term, $\varepsilon_i = v_i - u_i$. Here $v_i$ represents classic stochastic noise and captures model misspecification, measurement error, omitted variables, etc. $u_i \geq 0$ is investment inefficiency and acts to lower investment levels. Previous work has treated $\varepsilon_i = u_i$ and it is the omission of $v_i$ that can lead to a variety of complications in the interpretation of the second stage regression in Equation (2). Our treatment of $\varepsilon_i$ as being composed of two separate errors allows a more forceful and appropriate interpretation of investment inefficiency. Moreover, the estimation of this model can be easily accomplished using the stochastic frontier framework. To our knowledge, this marks the first attempt to use the stochastic frontier methodology to determine CSRs impact on investment inefficiency.

Even with the acknowledgement of two distinct components of $\varepsilon_i$, the impact of the determinants of inefficiency still needs to be accounted for. This too can be done in the confines of stochastic frontier analysis (SFA). This procedure explicitly characterizes the dependence of $u$ on $z_i$ and estimates the parameters of the relationship between investment inefficiency $u_i$ and $z_i$ together with the other parameters of the model. This can be accomplished using either a fully parametric stochastic frontier approach (Caudill & Ford, 1993, Caudill, Ford & Gropper, 1995, Kumbhakar, Ghosh & McGuckin, 1991) or a semiparametric model which avoids several potentially restrictive distributional assumptions (Parmeter, Wang & Kumbhakar, 2017, Simar, Van Keilegom & Zelenyuk, 2017, Tran & Tsionas, 2009).

### 3.2 The Parametric Stochastic Frontier Model

Let $\{Y_{it}, X_{it}, Z_{it}\}$ denote independently and identically distributed sample pairs of response for $i = 1, \ldots, N$ and $t = 1, \ldots, T$, where $Y_{it}$ is a scalar, $X_{it}$ is a $p$ dimensional vector of variables that compose the investment frontier, and $Z_{it}$ is a $q$ dimensional vector of exogenous determinants of investment inefficiency where $N$ denotes the number of firms and $T$ the number of time periods. The stochastic investment frontier is represented as:

$$Y_{it} = X_{it}'\beta + V_{it} - U(Z_{it}), \tag{3}$$

where $V_{it}$ is an idiosyncratic error term, with $E[V|X, Z] = E[V] = 0$, $Var(V|X, Z) = \sigma_V^2$ and $U(Z_{it}) > 0$ is the one-sided inefficiency term with $E[U|Z_{it}] = g(Z_{it}) \geq 0$.

The classical estimation approach for the stochastic investment frontier is, ignoring the presence of the determinants of investment inefficiency momentarily, to impose distributional assumptions for stochastic noise and investment inefficiency and deriving the likelihood function. The most common assumptions are

$$V_{it} \sim N(0, \sigma_V^2) \quad (4)$$

and

$$U(Z_{it}) = U_{it} \sim N^+(\mu, \sigma_u^2), \quad (5)$$

where $N^+(\cdot)$ is a positive truncation of the underlying Normal distribution. In the presence of determinants of investment inefficiency, the parameters of the truncated Normal distribution can be further parameterized, commonly in an exponential fashion, as

$$U(Z_{it}) \sim N^+(e^{Z'_{it}\gamma_1}, e^{Z'_{it}\gamma_2}). \quad (6)$$

When $\gamma_1 = \gamma_2$, this setup is known as the scaling approach and is a popular modeling framework in the area of efficiency analysis.

### 3.3 Semiparametric Stochastic Frontier Estimation

A key concern with application of the stochastic investment frontier model is the reliance on the distributional assumptions for $V_{it}$ and $U_{it}$. If either of these assumptions were to fail there is concern that the subsequent estimates may be invalid. It is instructive to note here that if the scaling approach specification is imposed in (6) the distribution of inefficiency can be multiplicatively decomposed into a function of the determinants of inefficiency and a random variable whose distribution has no dependence on these characteristics.

$$U(Z_{it}) = U_{it} \sim exp(Z'_{it}\gamma) \cdot N^+(\mu, \sigma_u^2). \quad (7)$$

With this framework, it is possible to relax the distributional assumptions and estimate expected inefficiency without requiring distributional assumptions. All model parameters can be recovered via nonlinear least squares (NLS) via

$$\left(\widehat{\beta}, \widehat{\gamma}^u, \widehat{\mu}^*\right) = \min_{\beta,\gamma,\mu^*} n^{-1} \sum_{i=1}^{n} \sum_{t=1}^{T} \left[Y_{it} - X'_{it}\beta + \mu^* e^{Z'_{it}\gamma}\right]^2. \quad (8)$$

Use of NLS offers the potential for more robust conclusions regarding observation specific inefficiency. However, there is still the issue of exactly how the determinants impact investment inefficiency, i.e. the exponential specification with a linear index may not be appropriate.

Recent advances in efficiency estimation have focused on relaxing the stringent distributional assumptions on noise and inefficiency. Tran & Tsionas (2009) proposed a semiparametric stochastic frontier model with an assumption that expected inefficiency depends on a set of covariates through an unknown but smooth function.[1] The model does not makes assumptions regarding the scaling property or the specific parametric distributions which govern $V_{it}$ and $U_{it}$(. Parmeter, Wang & Kumbhakar, 2017, Robinson, 1988, Tran & Tsionas, 2009). The stochastic frontier model with separable determinants of inefficiency is exactly the partly linear regression (PLM) model of Robinson (1988).

The key assumption for application of the PLM is $E[U|X,Z] = E[U|Z] = g(Z)$, known as the separability assumption. If the distribution of inefficiency depends on any of the traditional inputs of production then it is not possible to nonparametrically identify which part of the model corresponds to the production technology and which corresponds to inefficiency without imposing further restrictions (Parmeter, Wang & Kumbhakar, 2017, Tran & Tsionas, 2009).

The identification and estimation of the conditional mean of inefficiency is described as follows. Let $U^*_{it} = U(Z_{it}) - E[U|Z_{it}] = U_{it} - g(Z_{it})$, $\epsilon_{it} = V_{it} - U^*_{it}$. Thus, Equation (3) can be rewritten as:

$$Y_{it} = X'_{it}\beta - g(Z_{it}) + \epsilon_{it}, \quad (9)$$

and by assumption $E(\epsilon_{it}|X_{it}, Z_{it}) = 0$.

The principal interest is to consistently estimate expected investment inefficiency, $g(Z_{it})$, and its derivatives, $\bigtriangledown g(Z_{it})$, which represents the marginal effects of each of the determinants on investment inefficiency. The focus here is on the estimation of $g(Z_{it})$ without imposing distributional assumptions on $U(Z_{it})$, such as Half Normal or Truncated Normal, which is the common route with application of traditional stochastic frontier analysis.

The identification of $g(Z_{it})$ proceeds by noting that the model in Equation (9) is a PLM in the model of (Robinson, 1988). Once $\beta$ is estimated, $g(Z_{it})$ can then be estimated. $\beta$ is estimated as follows. Taking conditional expectations in Equation (9) we obtain

$$E(Y_{it}|Z_{it}) = E(X'_{it}|Z_{it})\beta - g(Z_{it}). \quad (10)$$

Subtracting Equation (10) from Equation (9), yields

$$Y_{it} - E(Y_{it}|Z_{it}) = (X_{it} - E[X_{it}|Z_{it}])'\beta + \epsilon_{it}, \quad (11)$$

[1] This approach is applied in Parmeter, Wang & Kumbhakar (2017) as well.

which we can write more compactly as

$$y_{it} = x_{it}'\beta + \epsilon_{it} \tag{12}$$

where $y_{it} = Y_{it} - E(Y_{it}|Z_{it})$ and $x_{it} = X_{it} - E(X_{it}|Z_{it})$. The conditional expectations $E(Y_{it}|Z_{it})$ and $E(X_{it}|Z_{it})$ can be consistently estimated using local-constant least-squares (Henderson & Parmeter, 2015, Li & Racine, 2007). Naturally, practitioners must pay careful attention to the bandwidths used to construct these quantities. We recommend using a data-driven approach, such as least-squares cross-validation (LSCV) to construct bandwidths. In our empirical results we use a Gaussian kernel to construct the weights with bandwidths selected via LSCV. $\beta$ is then estimated via ordinary least squares replacing $y_{it}$ and $x_{it}$ with their estimated versions.

Let $\varepsilon_{it} = Y_{it} - X_{it}'\hat{\beta}$ where $\hat{\beta}$ is our estimate from application of ordinary least squares applied to Equation (12). We then estimate the conditional mean of investment inefficiency ($g(Z_{it})$) as the conditional mean of $\epsilon_{it}$ given $Z_{it}$ via local-linear least-squares. The use of a local-linear estimator allow us to estimate gradients of the conditional mean inefficiency which are interpreted as the effect of each of the $Z$ variables on the conditional mean of inefficiency.

The PLM method is adept at estimating investment inefficiency and its determinants since the investment literature distinguishes real decision variables (that define the frontier) from financial friction variables (that define investment inefficiency). This method estimates unobserved maximum investment and determines the shortfall of actual investment from the maximum level. The shortfall indicates the presence of investment inefficiency which could be attributed to financial constraints due to information asymmetry.

# 4 Empirical Description

## 4.1 Model Specification

### 4.1.1 Investment frontier

Capital markets are imperfect due to informational problems, and capital investment is no longer determined only by fundamentals such as Tobin's Q and current and past sales (Fazzari & Petersen, 1993). All things equal, financing constraints limit investment below the neoclassical level. Therefore, the effect of capital market imperfections is one-sided and pushes investment to go below, but never above, the frictionless level. It is with this justification that financing constraints could be investigated using the SFA approach. With a neoclassical model describing the investment frontier, the level of financing constrained investment is evaluated as a deviation from the frontier, with the option of modelling the one-sided deviation as a function of firm characteristics (Wang, 2003). The degree of investment inefficiency is estimated using the difference between the frontier and the actual level of investment. This difference is attributed to investment inefficiency and it can be represented by a non-negative term $U_{it}$. In keeping with Wang (2003), a firm's investment decision can be defined as follows:

$$Y_{it} = X_{it}'\beta + V_{it} - U_{it}, \tag{13}$$

where $Y_{it}$ is defined as $\ln(I_{it}/K_{it})$; $X_{it}$: $\ln(Q_{it})$, $\ln(Sales_{it}/K_{it})$, $\ln(Sales_{it-1}/K_{it-1})$, $rGDP_{it}$, $rGDP_{it-1}$, and $\tau_t$. $I_{it}$ is the capital expenditures from the cash flow statement, $Q_{it}$ is Tobin's $Q$ for investment opportunities, $Sales_{it}$ is the net sales of firm $i$ in period $t$, $rGDP_{it}$ the growth rate of real GDP in the country the firm operates in and $\tau_t$ is a time trend. Note that investment and sales are divided by the firm's capital in order to control for size effects (Bhaumik, Das & Kumbhakar, 2012, Fazzari, Hubbard, Petersen, Blinder & Poterba, 1988, Wang, 2003).

The components of the vector $X_{it}$ in Equation (13) are based on the discussion that a firm's investment decisions depend on its future prospect, which is captured by Tobin's $Q$, and possibly also by its current and past sales in accord with the accelerator hypothesis of investment as sales captures the output effect (i.e., current sales promote current investment and predict future sales). The growth in real GDP helps to capture the economic environment the firm operates in.

The model in Equation (13) defines the stochastic frontier formulation of the investment function, and can be estimated using either the parametric or semiparametric techniques discussed earlier.

### 4.1.2 Firm characteristics

There exist many hypothesized variables which are assumed to impact the financial constraints of firms. Cash flow and total asset variables are routinely emphasized in the literature as significant factors affecting a firm's investment inefficiency (Parmeter, Wang & Kumbhakar, 2017, Wang, 2003). Regarding cash flow, firm's investments theoretically should be higher if it has a higher level of internal funds. Firms with larger assets are capable of providing collateral that in turn mitigates information asymmetry and eases financial frictions. On the contrary, firms with increased size might have lower investment opportunities. Including a variable capturing CSR allows us to determine the effect of CSR on the conditional expectation of investment inefficiency.

We accommodate these determinants of investment inefficiency into the model via $U(Z_{it})$ and our empirical model in Equation (13) where $Z_{it}$: $CSR_{it}$, $(CF_{it}/K_{it})$, $\ln(Assets_{it})$. $CSR_{it}$ is a corporate social responsibility score of firm $i$ in year $t$, $CF_{it}$ is the cash flow of firm $i$ in year $t$, and $Assets_{it}$ captures firm $i$'s fixed assets in year $t$. In order to control for size effects, all variables, except for $Assets_{it}$ and $CSR_{it}$ are divided by the firm's capital stock, $K_{it}$.

## 4.2 Data Description

We obtain financial data for our firms from the ORBIS database. These include investment defined as capital expenditures from the cash flow statement, Tobin's $Q$, sales, cash flow, and fixed assets. In order to control for size effects, all variables except fixed assets, are divided by the firm's capital. Data on the growth of real GDP (rGDP) is obtained from the World Bank database.

Data on CSR were obtained from Sustainalytics.[2] Sustainalytics is a database that provides the ESG ratings of companies across the world and can be used for research, investment decisions and other purposes. According to Sustainalytics, CSR broadly addresses companies' management systems, practices, policies, and other indicators reflecting environmental, social, and governance (ESG) performance of firms. CSR reflects a balanced view of performance on the environmental, the social and the corporate governance dimensions. The environmental dimension looks at how well a firm uses best management practices to deal with environmental risks and includes the categories: operations, contractors supply chain, and products and services. The social dimension is a reflection of how a company manages relationships with its employees, suppliers, customers and the communities where it operates with categories covering employees, contracts and supply chain, consumers, society and community and philanthropy. The governance dimension deals with a company's leadership, audits and internal controls, and shareholder rights. This dimension covers three categories: business ethics, corporate governance and public policy.

The dataset provided by Sustainalytics consists of detailed scores for the different indicators across Environment, Social and Governance dimensions of CSR performance. Sustainalytics groups firms into different peer industry groups and weights of indicators are uniquely defined for every peer group that reflects the relative importance given to the indicators. Every peer group is assessed across a fixed number of core indicators. In addition to the core indicators, sector-specific indicators are assigned to each peer group. For the core and sector-specific indicators, firms are assigned with a raw score between 0 and 100 where 0 denotes very poor performance and 100 denotes excellent performance. To construct overall CSR, as well as governance, social and environmental specific indices, we select the relevant indicators and aggregate them into a weighted score using the system of weights from the Sustainalytics dataset.

Table 1 presents the sample composition by industry. The dataset consists of an unbalanced panel of 1,462 firm-year observations of European listed companies for the period between 2009 to 2016. Manufacturing industries have the largest number of observations, with 534 observations comprising roughly 37% of our sample. The sample distribution shows that other industries, such as service or construction industries have a meaningful number of observations.

We winsorize the data at the 1st and 99th percentile levels to reduce effects of possibly spurious outliers. In Table 2, we report the summary statistics of the variables we use in our analysis, including the first quartile, median, third quartile, mean and standard deviation. CSR has a mean value of 55.28 and standard deviation of 19.726, indicating significant variation concerning CSR involvement.

**Table 1** Sample distribution across sectors

| Industry | Frequency | Percent |
|---|---|---|
| Agriculture forestry and fisheries | 25 | 1.71 |
| Mineral industries | 303 | 20.72 |
| Construction industries | 158 | 10.81 |
| Manufacturing | 534 | 36.52 |
| Service industries | 233 | 15.94 |
| Pharmaceuticals | 102 | 6.98 |
| Unclassified | 107 | 7.32 |

**Table 2** Descriptive statistics of variables

| | Description | Mean | SD |
|---|---|---|---|
| Investment Variables | | | |
| $\ln(I/K)$ | Investment to capital ratio | −1.250 | 1.135 |
| $\ln(\text{Tobin } Q)$ | Total market value divided by total asset value of a firm | −0.111 | 0.796 |
| $\ln(Sales/K)$ | Ratio of sales to capital | 1.558 | 1.047 |
| $\ln(Sales_{-1}/K_{-1})$ | Lagged ratio of sales to capital | 1.561 | 1.018 |
| $rGDP$ | Real GDP growth (annual percentage change) | 1.568 | 2.960 |
| $rGDP_{-1}$ | Lagged Real GDP growth (annual percentage change) | 1.398 | 3.095 |
| Determinants of Investment Inefficiency | | | |
| $CF/K$ | Free cash flow divided by capital | 0.845 | 1.863 |
| $\ln(Assets)$ | Natural log of total assets ratio | 15.458 | 1.589 |
| CSR | Score [0,100] | 55.280 | 19.726 |
| Governance | Score [0,100] | 15.250 | 5.938 |
| Social | Score [0,100] | 20.663 | 7.442 |
| Environment | Score [0,100] | 18.650 | 7.991 |

[2] http://www.sustainalytics.com/ "Sustainalytics is an award-winning global responsible investment research firm specialized in environmental, social and governance (ESG) research and analysis. The firm offers global perspectives and solutions that are underpinned by local expertise, serving both values-based and mainstream investors that integrate ESG information and assessments into their investment decisions."

**Table 3** Estimation results based on two stage approach

| | (1) | (2) |
|---|---|---|
| $\ln(Q)$ | 0.27 | |
| | (0.032) | |
| $\ln(Sales_t/K_t)$ | 0.216 | |
| | (0.097) | |
| $\ln(Sales_{t-1}/K_{t-1})$ | 0.279 | 0.527 |
| | (0.098) | (0.025) |
| $rGDP_t$ | 0.009 | |
| | (0.017) | |
| $rGDP_{t-1}$ | −0.001 | |
| | (0.012) | |
| Determinants of investment inefficiency | | |
| CF/K | 0.143 | 0.0009 |
| | (0.0146) | (0.016) |
| $\ln(Assets)$ | 0.078 | 0.006 |
| | (0.016) | (0.017) |
| CSR | −0.0102 | −0.006 |
| | (0.001) | (0.001) |

## 5 Results and Discussion

### 5.1 The Two Stage Approach

To reify our earlier discussion on the pitfalls of the two-stage approach for recovering the impact of CSR on investment inefficiency, Table 3 presents the coefficient estimates following the two stage approach of Biddle et al. (2009). The estimates in columns (1) and (2) are obtained following the procedure outlined in Biddle et al. (2009) with the only difference the specification of the investment model in the first stage. For the second stage we extracted the residuals and then ran a second regression on CF, CSR and $\ln(Assets)$.

There are several immediate facts that can be gleaned from Table 3. First, in both models, the estimated impact of CSR is negative and economically small. We also observe that both present sales and Tobin's $Q$ have positive and economically meaningful effects, suggest the potential for an omitted variable bias which then calls into question the second stage estimates. These effects can be clearly seen by look at the difference in the magnitudes of the estimates for the coefficients of all three variables in the second stage regression between columns (1) and (2).

### 5.2 The Stochastic Frontier Approach

Given both our theoretical discussion and our estimates from the two-stage approach, we now turn to our preferred stochastic frontier specification. The estimated parameters across several alternative stochastic frontier models are presented in Table 4. A key finding is that Tobin's $Q$ has a statistically significant coefficient at the 1% level with an elasticity of around 0.04–0.23, which is economically meaningful. This implies that one percent increase in Tobin's $Q$ is associated with 0.04–0.23% increase in investment to capital ratio. The NLS estimates consistent with Equation (8) indicate that cumulative sales are positively associated with firm investment. Looking at the partly linear estimates of Equation (9), the cumulative effect of sales are also positively associated with firm investment. Lagged sales is positively related with firm investment whereas current sales is negatively associated with investment.

This finding is consistent with the earlier estimates of Parmeter, Wang & Kumbhakar (2017), Bhaumik, Das & Kumbhakar (2012) and Abel & Blanchard (1986). Lagged sales have an estimated elasticity of around 0.13-0.80 across the various models. These estimated elasticities are interpreted as a one percent increase in lagged sales to capital ratio corresponds to a $0.13-0.80\%$ increase in the investment to capital ratio. The accelerator effect of sales on investment appears to have a time lag. The current and lagged economic environment appears to have an economically negligible effect on investment.

We now turn to the factors that alleviate or aggravate the friction from optimal investment, i.e. investment inefficiency. The coefficients of these variables are robust and consistent across estimation methodologies and specifications and, hence, are meaningful. Cash flow and asset size are shown to have an economically meaningful and positive association with the degree of investment inefficiency. This indicates that the most financially successful and least constrained firms in our sample do not rely on internal cash flow. The least financially constrained firms tend to utilize cheaper external funds and in turn are expected to have higher cash flows. Regarding size, large firms are more likely to have lower growth opportunities and tend to reduce investment activities (Benlemlih & Bitar, 2018). The lower growth opportunities with larger firms could explain why firm size is associated with high investment inefficiency.

The estimates across models which were used to analyze whether CSR performance is associated with investment inefficiency are shown in Table 4 under determinants of investment inefficiency. The estimated coefficient of CSR is negative and statistically significant, a finding consistent across all models. The negative coefficient indicates that a higher CSR score is associated with lower investment inefficiency. A plausible explanation for this is that firms with higher CSR enjoy lower information asymmetries and higher stakeholder solidarity improving management quality and helping to address financial constraints (mitigating investment inefficiency). This explanation is consistent with the findings of Cui, Jo & Na (2018) and Cho, Lee & Pfeiffer Jr (2013) that high CSR firms provide extra financial

**Table 4** Estimation results

| | SFA(No Z) | SFA(a) | SFA(b) | NLS(a) | NLS(b) | PLM (a) | PLM (b) |
|---|---|---|---|---|---|---|---|
| | Investment frontier parameters | | | | | | |
| $\ln(Q)$ | 0.23 | 0.125 | 0.124 | 0.194 | 0.194 | 0.078 | 0.042 |
| | (0.031) | (0.036) | (0.037) | (0.032) | (0.032) | (0.061) | (0.099) |
| $\ln(Sales/K)$ | 0.217 | 0.115 | 0.112 | 0.115 | 0.114 | −0.435 | −0.348 |
| | (0.094) | (0.077) | (0.088) | (0.09) | (0.09) | (0.124) | (0.206) |
| $\ln(Sales_{-1}/K_{-1})$ | 0.277 | 0.131 | 0.13 | 0.205 | 0.204 | 0.575 | 0.799 |
| | (0.094) | (0.082) | (0.092) | (0.09) | (0.091) | (0.12) | (0.221) |
| $rGDP$ | 0.009 | 0.009 | 0.009 | 0.007 | 0.006 | −0.013 | 0.012 |
| | (0.017) | (0.015) | (0.016) | (0.015) | (0.016) | (0.015) | (0.023) |
| $rGDP_{-1}$ | −0.0003 | −0.01 | −0.01 | −0.008 | −0.009 | 0.005 | 0.002 |
| | (0.012) | (0.011) | (0.012) | (0.011) | (0.011) | (0.009) | (0.01) |
| Determinants of investment inefficiency | | | | | | | |
| $CF/K$ | | 0.372 | 0.373 | 0.124 | 0.126 | | |
| | | (0.034) | (0.035) | (0.011) | (0.011) | | |
| $\ln(Assets)$ | | 0.038 | 0.036 | 0.044 | 0.044 | | |
| | | (0.018) | (0.019) | (0.007) | (0.007) | | |
| CSR | | −0.846 | | −0.612 | | | |
| | | (0.147) | | (0.096) | | | |
| GOV | | | −0.562 | | −0.48 | | |
| | | | (0.597) | | (0.355) | | |
| SOC | | | −1.347 | | −0.891 | | |
| | | | (0.532) | | (0.371) | | |
| ENV | | | −0.569 | | −0.47 | | |
| | | | (0.4598) | | (0.296) | | |

information that helps to reduce information asymmetry and provide a more accurate image regarding their performance.

There is also an emergence of numerous voluntary reporting standards that provide relevant information about companies' CSR practices and standardize their disclosure. In addition, third party disclosure on CSR performance provides new information beyond that reported by firms' voluntary CSR disclosures. Such disclosures increase firms' transparency that in turn, help to reduce information asymmetry (Cai, Cui & Jo, 2016, Cho, Lee & Pfeiffer Jr, 2013). A number of empirical studies have indicated the positive influence of information disclosures on investment efficiency (Biddle & Hilary, 2006, Biddle et al., 2009, Gomariz & Ballesta, 2014). The role of CSR can also be explained in light of the stakeholder theory. Freeman (2010) and Cornell & Shapiro (1987) argue that failing to meet stakeholders' expectations is more likely to generate market fears, which in turn will result in the loss of profit opportunities for the firm. CSR related multi-stakeholder welfare targets, may help to meet implicit claims of stakeholders and reduce information asymmetry, thereby decreasing investment inefficiency. Therefore, the implementation of CSR practices not only improve firms' sustainability but also enhances their competitive position (Samet & Jarboui, 2017, White, 2006).

The results of the two stage approach consistent with Equations (1) and (2) are included in the appendix for comparison. In the two stage procedure, we first estimate investment inefficiency and run the regression of estimated investment inefficiency (taken as the residuals from the first stage regression) on the hypothesized determinants. Looking at the results in the appendix, the two stage approach consists of estimates of the determinants which are smaller for the explanatory variables. This model understates the importance of CSR when explaining the association between CSR and investment inefficiency. This is consistent with the claim that ignoring the dependency of inefficiency and the determinants in the first stage would lead to under dispersed inefficiency estimates and the coefficients of the second stage are likely to be biased downward as indicated in (Parmeter & Kumbhakar, 2014) and (Wang, 2002).

Previous literature (Bouslah, Kryzanowski & M'Zali, 2013, Cook, Romi, Sanchez & Sanchez, 2019, Galema, Plantinga & Scholtens, 2008) e.g. suggests that aggregating dimensions of CSR may hide confounding effects among the individual dimensions. Therefore, it is useful to investigate the dimensions of CSR that matter the most in reducing firms' investment inefficiency. In order to better

**Table 5** Median estimated gradients of conditional inefficiency for NLS and PLM models. Upper and lower quartiles appear in parentheses beneath each median

| | NLS(a) | NLS(b) | PLM(a) | PLM(b) |
|---|---|---|---|---|
| CF/K | 0.189 | 0.189 | 0.731 | 0.283 |
| | (0.17, 0.207) | (0.170, 0.207) | (0.515, 0.960) | (−0.05, 0.593) |
| ln(Assets) | 0.067 | 0.066 | 0.013 | 0.034 |
| | (0.060, 0.073) | (0.059, 0.072) | (−0.050, 0.124) | (−0.086, 0.137) |
| CSR | −0.929 | | −0.715 | |
| | (−1.019, −0.838) | | (−1.350, −0.060) | |
| GOV | | −0.722 | | −0.667 |
| | | (−0.792, −0.651) | | (−3.666, 2.899) |
| SOC | | −1.340 | | −0.169 |
| | | (−1.470, −1.207) | | (−2.930, 2.451) |
| ENV | | −0.707 | | −1.122 |
| | | (−0.775, −0.636) | | (−3.718, 0.853) |

understand the dimensions that consistently impact investment inefficiency, we disaggregated CSR performance into its component dimensions and repeated our analysis. The results are reported in Table 4 as SFA(b) and NLS(b). We find that the social dimension has a negative and significant effect on investment inefficiency. However, both the governance and environmental components exhibit insignificant effects. One must be careful in interpreting these coefficients directly as they comprise an index effect, but they are still illusory as a first pass. Thus, the empirical results show that the key role of CSR in reducing investment inefficiency is mainly driven along the social dimension. In Cook, Romi, Sanchez & Sanchez (2019), they substituted the overall CSR score with six attributes of the CSR rating: human rights, employee relations, product characteristics, environment, diversity, and community. Four out of the six individual components of CSR negatively associated with investment inefficiency, namely employee relations, product characteristics, environment, and diversity. The human rights and community sub-dimensions do not significantly associate with investment inefficiency proxy. Our finding that social dimension plays the key role in reducing investment inefficiency is on contrary to the results of Cook, Romi, Sanchez & Sanchez (2019). One possible reason is the difference in the number of dimensions of CSR and how these dimensions are measured.

We investigate the gradients of the conditional mean inefficiency in order to properly compare the insights of the two main distribution free specifications (NLS and PLM). This is due to the fact that the nonlinear/nonparametric specification of the investment inefficiency function makes direct interpretation of a coefficient misleading. A more appropriate approach is to focus on the marginal change of the function, in essence acting as a local coefficient estimate. As it is expected that these marginal changes vary with the level of the covariates, Table 5 presents the median, upper and lower quartile estimates across the NLS and PLM models.

Table 5 shows the following insights. The impact of assets and cash flow on investment inefficiency is consistent across both the parametrically (NLS) and nonparametrically (PLM) specified inefficiency functions. While the magnitudes differ, both suggest that higher assets and free cash flow lead to high levels of investment inefficiency. Another consistent result across the two models is the impact of overall CSR. In both models CSR is negatively associated with investment inefficiency; firms with higher CSR scores have lower levels of investment inefficiency. Moreover, both the NLS and PLM models suggest a negative relation at the median between governance, social and environmental components, and investment inefficiency. Thus firms with higher performance across the CSR components have lower levels of investment inefficiency.

One aspect that does differ between the estimated marginal effects in Table 5 between NLS(b) and PLM(b) is the upper quartile. For NLS(b) these numbers are negative for GOV, SOC and ENV, while for PLM(b) they are all positive. This contrast in results could be attributed to several different factors. First, unlike PLM(a), where we have three covariates entering our nonparametric function, in PLM(b) we have five and this could lead to higher biases that exist. Second, the NLS specification could be incorrect and there are some firms, dependent upon their level of the CSR components, that actually see increased investment inefficiency as one or more of these scores improves.

While presenting the quartile estimates of the gradients provide meaningful insights into the partial effects of the various determinants of inefficiency, we can also graphically display all of the estimates, along with confidence bounds. Figure 1 presents a 45° plot of the gradients of the conditional mean of investment inefficiency for assets, cash

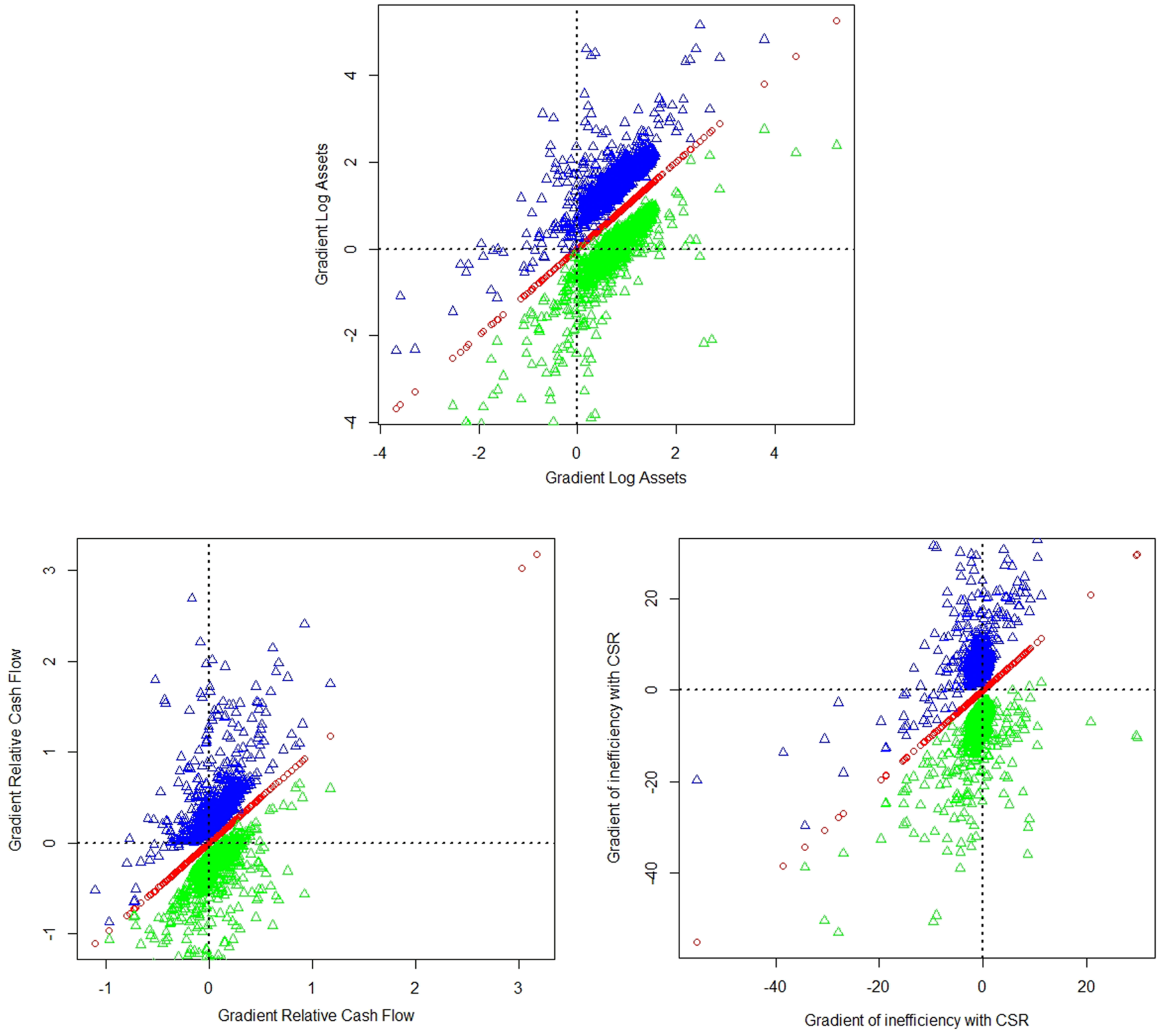


**Fig. 1** 45˚ plot of significant gradient effects for components of CSR. Significance is at the 95% level. Circles represent the gradient estimates while the triangles are the upper and lower bootstrap confidence interval

flow and CSR. 45˚ plots are useful tool to visualize results in nonlinear regression models.[3] The plot consist of the gradient estimates plotted against themselves (the 45˚ line) represented with circles together with their upper and lower confidence bounds (in this case the 95% confidence bound) represented with triangles. The majority of the significant effects for asset and cash flow are positive while the majority of the significant effects for CSR are negative. 21 of our 1,462 observations produced estimated gradients for firm assets which were negative and statistically significant. 16 of the 1,462 observations have estimated gradients for cash flow which are negative and statistically significant. Only two observations have estimated positive gradients for CSR which are statistically significant.

Looking at the direction of the estimated relationship, we find a negative relationship between CSR and investment inefficiency, a result consistent with the findings of the earlier literature. More specifically, Benlemlih & Bitar (2018) find that firms with higher levels of CSR are less prone to investment inefficiency. Deng, Kang & Low (2013) find that firms with higher levels of CSR engage in more valuable and efficient acquisitions. Cheung (2016) finds that firms with higher CSR scores have lower systematic risk, and El Ghoul, Guedhami, Kwok & Mishra (2011) find that CSR is negatively related with cost of capital. Improved monitoring of managerial actions and a better information environment should lead to enhanced decision making and greater capabilities for efficient investments, further buttressing our findings here.

[3] As noted in Henderson, Kumbhakar & Parmeter (2012), "These plots will easily allow the user to distinguish where a bulk of the effects lie, which effects are significant and which effects are insignificant."

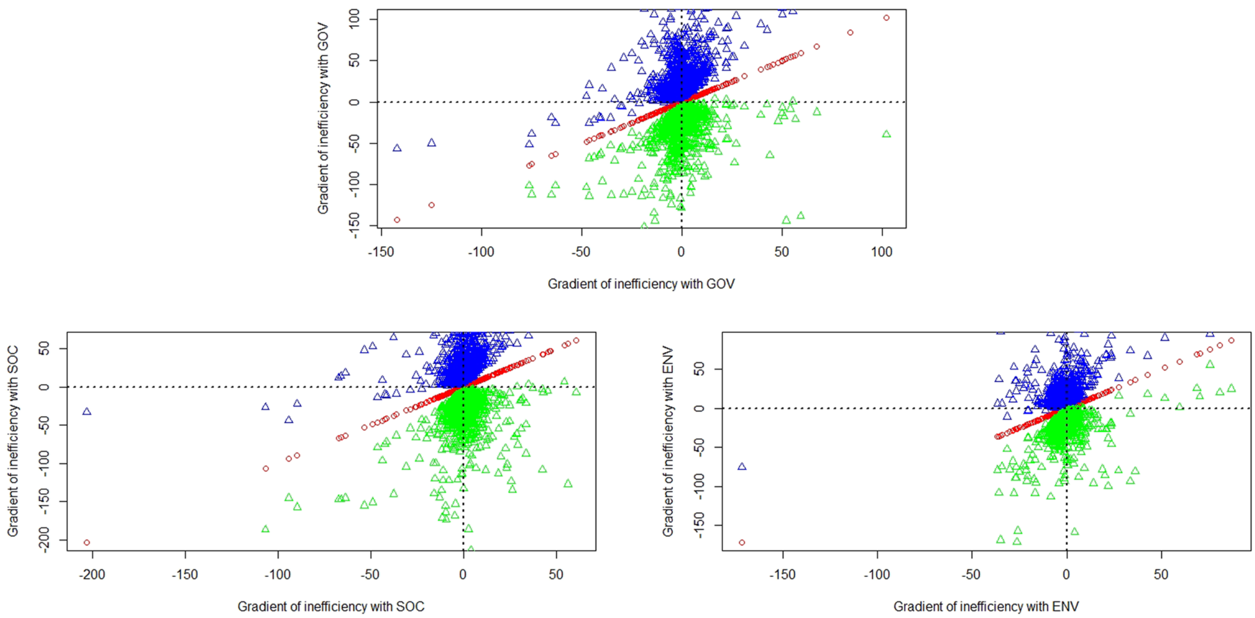


**Fig. 2** 45° plot of significant gradient effects for components of CSR. Significance is at the 95% level. Circles represent the gradient estimates while the triangles are the upper and lower bootstrap confidence interval

Figure 2 presents the 45° plot of the gradients of the conditional mean of investment inefficiency for the three dimensions of CSR: governance(GOV), social(SOC) and environmental(ENV) dimensions. The plots consist of the gradient estimates plotted against themselves (the 45° line) represented with circles, together with their lower and upper confidence interval (95% confidence interval) represented with green and blue triangles, respectively. All plots reveal substantial heterogeneity in the effects of these three covariates on investment inefficiency, with a majority of the significant effects being negative. Consistent with the literature reviewed in section 2, we find that firms with higher CSR have lower investment inefficiency. In other words, firms with higher CSR invest more efficiently.

## 6 Conclusion

We employ a semiparametric method to investigate the relation between CSR and firms' investment inefficiency. The model that we advocate stems from recent advances in semiparametric stochastic frontier analysis that do not require distributional assumptions on the composed errors. In other words, the stochastic frontier and the conditional mean of inefficiency are estimated without imposing any distributional assumptions. The main advantage of the semiparametric approach is that we are not only able to determine whether or not the average firm is financially constrained without imposing distributional assumptions, but we are also able to estimate a measure of the degree of the constraint for each firm and determine the marginal effect of corporate social responsibility on this measure.

The empirical analysis applies a sample of European listed companies, for the time period covering 2009 to 2016. This study provides strong and robust evidence that higher CSR performance is associated with lower investment inefficiency. This result strengthens the idea that high CSR firms enjoy low information asymmetry and high stakeholder solidarity, which may represent a source of competitive advantage and help to reduce investment inefficiency. The possible mechanism for presence of negative association between CSR performance and investment inefficiency could be through the role of CSR to provide extra information. Firms highly involved in CSR activities provide extra non-financial information that helps to reduce information asymmetry and provide a more holistic picture of performance. This study contributes to our understanding on the economic effects of CSR and provides arguments for relevant stakeholders including regulatory bodies to promote CSR initiatives.

The semiparametric stochastic frontier provides us with a powerful approach to investigate financial constraints and analyze relation with CSR. This approach requires less assumptions and involves much easier, faster and numerically more robust computations. A wider adoption of this approach is important to improve the investigation of financial constraints (investment inefficiency) that has grown interest since the financial crisis of 2008–2009.

An important practical implications can also be derived from results of this study that the development and implementation of CSR strategies is crucial to improve firm growth

**Table 6** Estimation results based on two stage approach

| | Model (1) | Model (2) | Model (3) |
|---|---|---|---|
| ln(Tobin Q) | 0.23 | 0.027 | |
| | (0.031) | (0.032) | |
| $\ln(Sales_t/K_t)$ | 0.217 | 0.216 | |
| | (0.094) | (0.097) | |
| $\ln(Sales_{t-1}/K_{t-1})$ | 0.277 | 0.279 | 0.527 |
| | (0.094) | (0.098) | (0.025) |
| $rGDP_t$ | 0.009 | 0.009 | |
| | (0.017) | (0.017) | |
| $rGDP_{t-1}$ | −0.0003 | −0.001 | |
| | (0.012) | (0.012) | |
| | Determinants of investment inefficiency | | |
| CF/K | 0.0001109 | 0.143 | 0.0009 |
| | (0.0000117) | (0.0146) | (0.016) |
| $\ln(Assets)$ | 0.000064 | 0.078 | 0.006 |
| | (0.0000128) | (0.016) | (0.017) |
| CSR | −8.12e−06 | −0.0102 | −0.006 |
| | (1.04e−06) | (0.001) | (0.001) |

and safeguard interests of different stakeholders. Therefore, firms' need to integrate social and environmental issues in their strategies as they helps to move towards decisions that are better for the business and the society. While our research design exploits the variability of CSR to explain the variability in investment inefficiency, we recognize that our analysis may be primarily capturing cross-sectional differences (pooled cross-sectional). The limited yearly data prevents us from exploiting dynamic relationships between CSR and investment inefficiency.

## Compliance with ethical standards

**Conflict of interest** The authors declare no competing interests.

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## 7 Additional Results Based on Two-Stage Approach

In Model 1, the first stage uses SFA to obtain investment inefficiency and we ran a regression to see the association between CSR and the inefficiency which are presented in Table 6. Model 2 and Model 3 follow the two stage approach of Biddle et al. (2009). We extracted residuals using the OLS estimates of the investment model then ran a second regression on CF, CSR and $\ln(Assets)$. Model 3 estimates investment level in the following year as a function of growth opportunities in the current year as measured by sales.

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