International Journal of Economic Behavior and Organization
2025, Vol. 13, No. 1, pp. 20-34
https://doi.org/10.11648/j.ijebo.20251301.13

Review Article

Effect of Research and Development (R&D) on Company Performance in Cameroon: An Application of the Generalized Propensity Score

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Abstract

R&D expenditure is a must for any company wishing to remain competitive and sustainable in this globalized world. However, they need to be controlled to ensure that they do not have a rather unfavorable effect due to market uncertainty. For this reason, this article analyzes the effect of R&D on company performance in Cameroon. The latter is measured by value added on the one hand, and net profit on the other. The study is based on a sample of 162 Cameroonian companies having invested in Research and Development (R&D). This sample is taken from the survey on the determinants of business performance in sub-Saharan Africa carried out in 2014 by the International Development Research Centre (IDRC). The results of the generalized propensity score estimation show that in Cameroon, company performance indicators grow monotonically as R&D expenditure increases These results are confirmed by the robustness analysis performed by applying the Generalized Propensity Score under the generalized linear and quantile approach. Thus, companies in Cameroon need to take advantage of government R&D subsidies and appropriate the results of research carried out in universities and research centers, and train their employees on an ongoing basis to promote R&D within the company and improve performance.

Keywords

R&D, Value Added, Profit, Dose-response, Covariates

1. Introduction

The market economy policies adopted by most countries worldwide, driven by businesses aiming to enhance their performance, undoubtedly create opportunities but also present challenges. A notable example is the increasing strain on economic systems caused by the growing complexity of cross-border networks facilitating the flow of knowledge, ideas, and technologies [68]. To mitigate these costs while delivering low-cost products with superior or more innovative characteristics than those of their competitors, companies must effectively acquire, absorb, and adapt these flows. Research and Development (R&D) activities, therefore, serve as a strategic lever for companies seeking to boost their performance and position themselves as world-class organizations [37]. This phenomenon could explain the surge in R&D activity since 2019, marked by an exceptional global growth rate of 8.5% [54]. Moreover, despite the economic slowdown triggered by the COVID-19 pandemic, companies increased their R&D investments by approximately 10% in 2020 [54].

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Received: 23 December 2024; **Accepted:** 10 January 2025; **Published:** 12 February 2025

Similarly, labor productivity saw a 2.2% growth between 2010 and 2020 [54].

In Africa, while innovation is critically important for development, 70% of countries on the continent fail to invest even 1% of their GDP in R&D funding [10]. This underinvestment significantly limits their ability to foster new creations and absorb technologies from other regions. Consequently, the performance of African businesses has lagged behind their counterparts in developed countries over the past decade [10]. Cameroon, like many sub-Saharan African countries, is not exempt from this observation. Urbanization in Cameroon is diversifying dietary patterns and stimulating the domestic market [65]. As a result, Cameroonian companies are engaging in technological research not only to develop new products but also to adapt imported technologies to local conditions [65]. The Ministry of Scientific Research and Innovation supports these efforts by strengthening the protection of industrial property rights and promoting technological development support structures [68].

However, in terms of R&D expenditure, Cameroon, at 0.34%, lags behind Senegal (0.51%) and Côte d'Ivoire (0.53%) [68]. Despite this relatively low percentage, it is worth noting that the value-added growth of Cameroonian businesses was 1.7% in 2017, compared to -3.9% in 2016 according to the 2019 report from the National Institute of Statistics. Additionally, the financial profitability rate improved from 2.9% in 2016 to 3.9% in 2017, following a dip to 4% in 2015 according to the 2019 and 2021 reports from the National Institute of Statistics. Given the above, it is evident that although Cameroon's R&D expenditure remains relatively low, business performance indicators are showing signs of improvement. This raises the critical question: what is the impact of R&D expenditure by Cameroonian companies on their performance? We propose and defend the following hypothesis: R&D expenditure positively impacts the performance of Cameroonian companies.

Research and experimental development (R&D) comprises creative and systematic activities aimed at increasing the stock of knowledge and creating new applications for existing knowledge (OECD, 2015) [53]. To this end, the analysis of R&D activities in companies distinguishes between two types of decision: whether or not to invest in R&D and the decision on the level of expenditure to be committed to investment in R&D. This second approach is favoured in this work as it allows us to define the different R&D investment tranches. Company performance is analysed in this work from a microeconomic perspective, which, following Schmalensee (1989) [60] presents it as the creation of value. Thus, even if several other indicators are found in the literature, value added and realised profit are used as indicators to measure company performance in this study. This is justified by the fact that they are less volatile and make it possible to measure the wealth created by companies for the economy as a whole and to distribute dividends to the various shareholders, respectively (D'Attoma & Pacei, 2016 [22]; Schmalensee, 1989 [60]).

Theoretically, R&D ensures the performance of companies by reducing production costs, innovation, externalities and the capacity to absorb new technologies (Griliches, 1979 [29]; Hanel & St-Pierre, 2002 [35]; Thompson, 2001 [66]). From an empirical point of view, there are two approaches: the first, described as direct, analyses the effect of R&D on company performance without taking into account any other moderating or transition variable (Griliches, 1979 [29]; Hall et al, 2010 [34]; Segarra & Teruel, 2011 [62]); the second (and most abundant) indirect approach evaluates the effect of R&D on company performance via innovation (Crepon et al., 1998) [21]. However, there are few studies (Alene, 2010 [6]; Mulugeta, 2022 [50]) that address this issue in the specific context of sub-Saharan African countries. This can be attributed to the lack of official survey data on companies, the low level of investment in R&D (Tsambou & Fomba Kamga, 2021) [68] and the fact that innovation does not necessarily come from R&D activities in these countries (Egbetokun et al., 2016 [25]; Le Bas & Molou, 2020 [44]). For this reason, a direct approach to the effect of R&D on business performance in these countries needs to be examined. Cameroon obeys this logic, as few studies exist there and the authors find a direct positive effect of R&D spending on business performance (Djoutsa Wamba et al., 2017 [24]; Fambeu & Messomo, 2020 [27]; Mboe Bobo et al., 2020 [49]) without, however, taking into account the level of R&D spending.

R&D investment is not allocated to firms at random, but rather is determined by firm decisions, implying that firms have a strong self-selection to invest in R&D (Mulugeta, 2022) [50]. This question raises the problem of selection bias, which most studies address using propensity score matching (PSM), fixed effects models (Mulugeta, 2022) [50], quartile regression (Mboe Bobo et al., 2020 [49]; Segarra & Teruel, 2011 [62]). Unfortunately, the latter do not assess the effect of R&D spending levels on company performance. This article makes a methodological contribution, since it applies generalised propensity score matching methods to Cameroon. This provides a general understanding of the increase in firms' value added and profit in response to each level of increase in R&D investment.

The empirical test of our hypothesis is carried out in a sample of 162 companies from the International Development Research Centre (IDRC) survey conducted in 2014. We use a dose-response regression under the linear and generalised linear approach as in the work of Li et al., (2018) [45] and robustness is analysed by the generalised propensity score for continuous treatment effects by quantile (Alejo et al., 2020) [4]. Overall, our results show that R&D expenditure and the two performance indicators grow monotonically. In the remainder of the article, section 2 provides an overview of the literature, while sections 3 and 4 are devoted to presenting the methodology and analysing the results, respectively.

2. Literature Review

The effect of R&D on business performance has been studied following the seminal contributions of Griliches. However, these studies are far more conclusive in developed countries than in developing countries. Without being exhaustive, these studies are conducted more in the United States of America (Ehie & Olibe, 2010 [26]; Jacques & Mairesse, 1985 [40]; Mansfield, 1980 [47]), in France (Hall & Mairesse, 1995 [33]; Mairesse & Cunéo, 1985 [46]), Germany (Harhoff, 1998) [36], Canada (Hanel & St-Pierre, 2002) [35] and OECD countries (Verspagen, 1995) [72]. The theoretical analysis of the effect of R&D on business performance is based on the theory of innovation and its diffusion (Chesbrough, 2003[19]; Rogers, 1962 [58]; Schumpeter, 1942 [61]; Urban & Von Hippel, 1988 [71]), the theory of resources and capabilities (Barney, 1991) [11], the theory of learning (Argyris & Schön, 1997) [8] and the microeconomic implications of the theory of endogenous growth (Romer, 1990 [59]; Thompson, 2001 [66]). However, the empirical evidence is mixed, since it shows respectively positive, negative and neutral effects of R&D on company performance (Mulugeta, 2022) [50].

The positive effect stems from the fact that R&D activities confer a temporary monopoly on the companies that adopt them. This can be explained either by companies' competitive advantage or by the externalities of R&D activity (Hall et al., 2010 [34]; Hanel & St-Pierre, 2002 [35]). Competitive advantage means that R&D enables companies to improve the quality or reduce the average production costs of existing products (Hall et al., 2010) [34]. Furthermore, R&D carried out by one company can produce positive externalities for other companies. Such externalities are total and significant, the closer the sender of the R&D and the receiver are (Hall et al., 2010) [34]. To this end, two types of externalities enable R&D activities to have a positive influence on company performance: financial and non-financial externalities. Financial externalities arise from the sale of new or significantly improved intermediate or capital goods to other firms at prices that reflect at least the full value of the technical progress incorporated into them (Hall et al., 2010) [34]. Non-monetary externalities arise from the diffusion of knowledge from the R&D activities of other companies and used by any company. In this vein and for large companies in the European Union, Ortega-Argilés et al, (2011) [56] on panel data from 532 observations over six years (2000-2005) find that R&D spending has a positive influence on company productivity. Moreover, according to these authors, the coefficients of this influence increase monotonically when there is mobility of companies from the low technology intensity sector to the medium sector and finally from the latter to the high technology intensity sector. In the same vein, Ortega-Argilés et al., (2015) [55] using a unique longitudinal database of 1809 US and European manufacturing and service firms over the period 1990-2008, find that the stock of knowledge has a significant positive impact on firm productivity in R&D-using service sectors. Similarly, Aguiar & Gagnepain (2017) [2] find that the participation of European firms in research activities increases labour productivity but has a limited effect on marginal profit; For OECD countries, Ugur et al., (2016) [70] using a meta-regression of 1253 estimates from 65 primary studies find that, the rate of return on R&D and the average elasticity are positive in OECD Countries but to a lesser degree and do not differ significantly despite theoretical predictions of higher social returns. The results of Andrade et al., (2018) [7] on 6,028 observations between 2003 and 2013 worldwide show that, the closer companies get to the technological frontier, the higher the return on R&D investment on performance.

For individual countries: Segarra & Teruel (2011) [62], after exploding R&D expenditure from internal and external sources on a sample of 1,612 Catalan companies in Spain, use OLS and quantile regression models on individual data to find that the marginal effect of internal R&D on company productivity decreases as productivity rises, whereas the marginal effect of external R&D tends to increase; Sharma (2012) [63] finds that R&D intensity has a significantly positive effect on the total productivity of factors in the pharmaceutical industry in India over the period 1994-2006; Bond & Guceri (2016) [15] on large British establishments over the period 1997-2008 show that there is a significant positive relationship between current productivity and past R&D expenditure; on 1506 Chinese manufacturing companies, Guo et al., (2018) [32] use OLS regression to show that R&D expenditure has a positive effect on the three indicators of future performance (ROA, ROE and Tobin's Q) provided that the company uses the differentiation strategy. Using a generalised propensity score matching approach with continuous treatments on 2097 Chinese firms over the period 2008-2017, Dai et al., (2019) [23] find that research and development activities are found to be complementary in promoting firm performance and suggest the existence of optimal proportions of R&D components to maximise firm performance. Tung & Binh (2021) [69] on panel data from 343 companies over the period 2010-2018 and applying fixed effects and double least squares, find that R&D expenditure has a significantly positive effect on sales, profits, financial profitability and the economic profitability of companies in Vietnam.

For sub-Saharan African countries we have : In Nigeria and although only 35 firms out of a sample of 207 invested in R&D, Adeyeye et al., (2013) [1] find through OLS regression that, R&D expenditure of service firms have a positive and significant effect on their performance. Similarly, Chukwumaeze et al., (2018) [20] on panel data find that over the period 2008-2017, R&D expenditure measured by R&D intensity has a significantly positive effect on the financial performance of firms measured by return on assets. On a sample of 476 firms in Ethiopia and based on regressions using fixed effects methods, the Propensity Score and the endogeneity effect treatment Mulugeta (2022) [50] finds that

R&D activities (dichotomous variable) have a positive influence on firms' long-term financial performance. The literature on Cameroon is limited to three known studies. Djoutsa Wamba et al., (2017) [24], using panel regressions over the 2004-2011 period, find that innovation capacity, approximated by R&D spending, has a positive impact on firm performance, regardless of the indicator used (return on assets, return on equity and labour productivity). In the same vein, Mboe Bobo et al., (2020) [49] apply quantile regression to a sample of 40 companies that have filed their FSDs and find that R&D expenditure has a significant positive effect on value added and return on assets. On the other hand, Fambeu & Messomo (2020) [27] find a neutral negative effect of the R&D investment decision on performance indicators on a sample of 1008 industrial firms drawn from the survey conducted in 2009 by the Institut National de la Statistique (INS) in Cameroon.

The negative effect stems from the fact that investment in R&D may not automatically create value for the companies that invest in it (Alam et al., 2020) [3]. This can be explained by agency conflict or commercial risk. Agency conflict, as suggested by (Jensen & Meckling, 1976) [42], can restrict the benefits derived from R&D investment. Based on the free cash flow hypothesis, managers may overspend their free cash flow on projects such as R&D (Jensen, 1993) [41]. This overinvestment can lead to value destruction in R&D projects and may be the result of the failure of internal control systems (Alam et al., 2020 [3]; Jensen, 1993 [41]). Finally, investment in R&D increases the probability of introducing product and process innovations, but the probability that such investment will sufficiently increase company performance is less than 1 (Baumann & Kritikos, 2016) [12]. Thus, because of the technological and economic uncertainty that such investments entail, companies may run the risk of bankruptcy because of the negative return on their R&D investment. This may be due either to the non-commercialisation of new products or processes resulting from research or to technological imitations which limit the return on investment (Baumann & Kritikos, 2016) [12]. In an empirical analysis, Shin et al., (2017) [64] find a negative relationship between R&D ratio and net margin for the whole sample, suggesting that industry may be overinvesting in R&D. Chen et al., (2019) [18] have based data on Taiwanese semiconductor industry firms for the period 2005-2016, that large R&D investments in one period may reduce firm performance in the same period and continue to influence it in subsequent periods; On a sample of 3,399 Slovenian companies observed between 2012-2016, Ravšelj & Aristovnik (2020) [57] show that the intensity of R&D spending has a negative effect on the short-term performance of companies due to the uncertainty and risk inherent in R&D activities. On a sample of 476 firms in Ethiopia Mulugeta (2022) [50] finds that R&D activities (dichotomous variable) negatively influence the short-term financial performance of firms. Arif Khan et al., (2023) [9] Using a sample of Chinese companies listed on the stock exchange between 2000 and 2020, reveal that company performance decreases as R&D expenditure increases, the impact being less pronounced for state-owned companies. The negative impact of R&D on company performance is also mitigated in the event of intense competition.

Lastly, the neutral effect is the case where R&D expenditure is equal to the revenue from the temporary monopoly or the return on the related investment is random (Niklas & Wikberg, 2015) [51]. In addition, linear and non-linear relationships between R&D and firm performance are highlighted. Yeh et al., (2010) [74] confirm the existence of a single threshold effect and show an inverted U-shaped correlation between R&D intensity and firm performance in Taiwan; the results of the work of Xu & Jin (2016) [73] show that, on a sample of 30 listed firms in China, R&D has a neutral effect on current firm performance, whereas this effect becomes negative when R&D expenditure is cumulated and has a positive effect on lagged marginal profit. In Cameroon Nkakene Molou (2017) [52] on a sample of 101 companies finds that R&D expenditure, taken individually, has no statistically significant effect on the value added of companies in Cameroon; Insee & Suttipun (2023) [39] show that even if R&D expenditure is not directly related to company performance, there is a positive relationship between R&D expenditure and company performance, mediated by the competitive advantage of Thai private companies.

Thus, most of the studies presented above confirm a positive effect of R&D. However, the above review of the literature shows that most studies have focused on the effect of either the R&D investment decision or the intensity of R&D spending on firm performance. However, few studies analyse the effect of the level of R&D investment, which is the main contribution of this study.

3. Methodological Framework

In this paper, the treatment is the allocation of R&D expenditure. Therefore, firms with positive R&D spending are assigned to treatment groups with different spending levels (Li et al., 2018) [45]. We assume that R&D spending depends on observed factors such firm size, firm age, exports, manager experience, region and industry. Controlling for these observed confounding factors, it is normally assumed that value added and profit are independent of the level of R&D expenditure. We estimate the effects of R&D expenditure on value added and profit using the Generalised Propensity Score (GPS) and the dose-response function in accordance with Bia & Mattei [14] and Li et al. [45]. By design, firms in the different treatment levels are identical according to the predefined factors used to estimate the GPS, and they differ only in the allocation of their R&D expenditure. Using this method, biases (such as aggregation bias, misspecification bias and simultaneity bias) are assumed to be handled through the research design and non-conformity assumption (Li et al., 2018) [45]. But, categorisation or discretisation of continuous treatments usually leads to a number of serious problems, such as loss of test power, classification errors, prediction problems and even interpretation of results and coefficients of interest (Alejo et al., 2018) [5]. Therefore, robustness is analysed in this paper by the generalised propensity score for quantile continuous treatment effects proposed by (Alejo et al., 2018 [5], 2020 [4]).

3.1. Configuration

Consider a sample of companies indexed by i = 1, N in our sample; for the sake of simplicity, the observation index i is omitted. Let t be the different levels of R&D treatment and T the continuous treatment space with the interval $[t_0, t_1]$. Let X be a vector of pre-treatment covariates that are used to estimate the GPS. Y_t corresponds to a level of performance specific to a level of R&D expenditure treatment. GPS is calculated as the conditional density of the R&D treatment on the pre-treatment covariates (Li et al., 2018) [45]. It is denoted according to Hirano & Imbens [38] and Li et al., (2018) [45] by: $R = r(T, X)$, where$r(t,x) = f_{T|X}(t|x)$. This method is based on certain assumptions (Li et al., 2018) [45] including:

Low non-foundation

Also known as selection on observables, this assumption guarantees the random adoption different levels of R&D spending, conditional on the observed covariates before treatment (Hirano & Imbens, 2004) [38]. Given the definition of GPS$r(t, X)$ and the absence of a weak foundation, the allocation of the treatment to R&D spending is independent of the estimated generalised Propensity Score: $Y(t) \perp T|X$ (Hirano & Imbens, 2004) [38]. In other words, firms with the same Generalised Propensity Score (SPG) have the same density function of firm characteristics and, consequently, the selection of the level of R&D expenditure is random provided they have the same SPG. To this end, Hirano & Imbens [38] prove that the GSP can eliminate the bias resulting from differences in the pre-treatment covariates. Consequently, the dose-response function is $\beta(t, r) = E[Y(t)|r(t, X) = r] = E[Y|T = t, R = r]$ and $\mu(t) = E[\beta(t, r(t, X))]$, where$\beta(t, r)$ and$\mu(t)$ represent, respectively, the conditional expectation of the outcome and the dose-response function. Although the weak non-foundation hypothesis cannot be tested directly, the rich set of pre-treatment covariates makes the method plausible. Similarly, the possibility that other unobserved factors influence both R&D expenditure and profit and value added should not be ruled out. The GSP cannot take unobserved factors into account. Therefore, there may always be some level of selection bias in the estimators, although it is much smaller than any direct regression on performance indicators (Li et al., 2018) [45].

Weak conditional independence

It ensures the random adoption of different levels of R&D spending conditional on the observable economic characteristics of firms. It is therefore necessary to place ourselves in a case where the assignment of R&D expenditure is based on the observable characteristics of firms and is therefore independent of potential outcomes (Bouayad-agha et al., 2018 [16]; Hirano & Imbens, 2004) [38]: $Y(t) \perp T|X$. Thus, the GSP corrects for the bias resulting from differences in covariant pretreatment. Consequently, the dose-response function is:

$\beta(t, r) = E[Y(t)|r(T, X) = r] = E[Y|T = t, R = r]$ and $\mu(t) = E[\beta(t, r(t, X))]$, where$\beta(t, r)$ and$\mu(t)$ remain the conditional expectation of the out come and the dose-response function, respectively.

Balance of score between control variables (balancing hypothesis)

This assumption guarantees the equilibrium of the pre-existing means of companies at each R&D expenditure interval. This implies that firms within the same Generalized Propensity Score (GPS) R&D expenditure interval are similar in terms of observable characteristics, regardless of their level of treatment. Among the 162 R&D spenders, we divide the range of R&D spending into four (04) treatment intervals, each representing about 25% of the total sample. More precisely, the treatment intervals are: $[1 - 160];]160 - 800];]800 - 8000]$ and $]8000 - 700000]$. The pre-treatment covariates are generally very different between observations at different R&D levels. Subject to the estimated GPS, the adjusted means of the preprocessing covariates between observations at each treatment level should not be statistically different (Li et al., 2018) [45].

3.2. Estimation Strategies

The main objective of the empirical strategy is to estimate the dose-response function and to examine the effects of different levels of R&D expenditure on the performance indicators of firms in Cameroon. To obtain the dose-response function, it is necessary to estimate the GSP and the result of the performance indicators Y(t) on the basis of the R&D treatment variable and the GSP estimated in the order (Bia & Mattei, 2008) [14]. In reality, the estimation of the dose-response function begins with an auxiliary regression which estimates the different levels of R&D expenditure after controlling for observable characteristics $T_i = X_i\beta_i + \varepsilon_i$

This makes it possible to calculate a generalised propensity score from the estimated parameters, which is no longer written as a probability but as a density of R&D expenditure levels conditional on observable firm characteristics (Bouayad-agha et al., 2018) [16]. Subsequently, the technical details of the estimation of the GPS and dose-response functions using the ordinary linear approach and the GLM approach, are represented respectively (Li et al., 2018) [45]. For the robustness analysis, we adopt the approach of Alejo et al., (2020) [4].

The ordinary linear approach

It assumes that the conditional level of R&D expenditure follows a normal distribution:

$T|X \sim \{\beta_0 + \beta_1 X, \sigma^2\}$. The parameters, $\beta_0 \beta_1$ and σ^2 are estimated using maximum likelihood (Li et al., 2018) [45]. Thus, according to Hirano & Imbens (2004) [38] and Bia &

Mattei (2008) [14] the generalised propensity score (GPS) is modelled as follows:

$$\text{GPS} = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left[\frac{1}{2\hat{\sigma}^2}\left(\text{T} - \hat{\beta}_0 - \hat{\beta}_1 \text{X}\right)^2\right] \quad (1)$$

We verify that this generalised propensity score effectively balances the control variables and thereby eliminates the selection bias on observable characteristics (Bouayad-Agha et al., 2018) [16]. After obtaining the GSP, we need to estimate the performance expectation E(Y|T, R), conditional on the level of treatment of R&D expenditure and the estimated GSP. The polynomial second-order treatment of the variable and the GSP are introduced into the model to obtain the following non-linear specification (Hirano & Imbens, 2004 [38]; Li et al., 2018 [45]):

$$\varphi\{E(Y|T, SPG)\} = \alpha_0 + \alpha_1 T + \alpha_2 T^2 + \alpha_3 GPS + \alpha_4 GPS^2 + \alpha_5 T * GPS \quad (2)$$

$\varphi\{.\}$ is a function related to the continuous nature of firm performance. The quadratic form is applied given a potential non-linear relationship between R&D expenditure and firm performance (Li et al., 2018) [45]. The dose-response function is obtained by estimating the potential average firm performance at different levels of R&D expenditure

$$E\{\widehat{Y(t)}\} = \frac{1}{N}\sum_{i=1}^{N} \hat{\beta}\,\{t, \hat{r}(t, X)\} \quad (3)$$

Combining the last two equations, we obtain (Hirano & Imbens, 2004) [38]:

$$E\{\widehat{Y(t)}\} = \frac{1}{N}\sum_{i=1}^{N} \hat{\alpha}_0 + \hat{\alpha}_1 T + \hat{\alpha}_2 T^2 + \hat{\alpha}_3 \widehat{SPG} + \hat{\alpha}_4 \widehat{SPG}^2 + \hat{\alpha}_5 T * \widehat{SPG} \quad (4)$$

Generalized linear model

As a measure of robustness, the GPS is also estimated using the GLM approach to obtain the dose-response function. The purpose of estimating the GLM approach is to test the sensitivity of the results to different specifications for the distribution of R&D expenditure. The general estimation process follows the same sequential steps as the ordinary linear approach (Li et al., 2018) [45]. Essentially, the main difference between the ordinary linear approach and the GLM approach lies in the distribution assumptions of the treatment variable (i.e. R&D expenditure does not necessarily follow a normal distribution) and in the linear relationship of the covariates and the (possible) transformation of the mean of the R&D expenditure treatment variables [30]. More specifically, the GLM approach allows for flexible distribution assumptions of R&D spending, which also take into account a potentially wide range of non-normal distributions of R&D spending (Guardabascio & Ventura, 2013 [30], 2014 [31]). These two properties are formalised as follows:

$$f(T) = c(T, \emptyset) exp\left\{\frac{T\theta - a(\theta)}{\emptyset}\right\} \text{ and } \quad g\{E(T)\} = \beta X,$$

where$a(\theta)$ denotes the distribution function in the exponential family and $g\{.\}$ denotes the link function (Guardabascio & Ventura, 2014) [31]. The parameters (∅, θ) are associated with certain distributions in the exponential family. In order to test the robustness of the results, we specifically incorporate, a Gamma, negative binomial and logit frationary distribution inspired by the work of Li et al., (2018) [45]. Thus, following Guardabascio & Ventura (2014) [31], GPS is estimated as follows:

$$\widehat{R_i} = \text{r(T,X)} = c(T, \hat{\emptyset}) exp\left\{\frac{T\hat{\theta} - a(\hat{\theta})}{\hat{\emptyset}}\right\} \quad (5)$$

Generalized propensity score for continuous treatment effect per quantile

The aim here is to present the two-step implementation of this model on stata using the qcte command, based on the work of Alejo et al., (2020) [4]. The estimators are implemented as two-step estimators. In the first step, one estimates a ratio of conditional densities. In the second step, one performs a simple weighted quantile regression estimation where the weights are given by the ratio of conditional density functions (Alejo et al., 2020) [4]. According to the latter, Alejo et al., (2018) [5] show the uniform consistency and low convergence of this two-step estimator. In this section, we focus on inference on the quantile dose-response functions (QDRF) and the quantile continuous treatment effect (QCTE). An important parameter of interest when the treatment is continuous is the QDRF and The QCTE is defined as the difference of the τth quantile at different levels of treatment. First, to test the QDRF, we consider the general null hypothesis

$$H_0: q_{ro}(t) - r(t) = 0 \text{ with } \ t \in T$$

where r(t) is assumed to be known, continuous in t over T, and$r\epsilon l^{\infty}(T)$. Inference is performed uniformly over all levels of processing, T. The basic inference process is as follows:

$$Q_n(t) = \hat{q}_\tau(t) - r(t) \text{ With } \ t \in T \quad (6)$$

The general assumptions on the vector$q_\tau(t)$ can be taken into account by functions of. $Q_n(.)$ Consider the Kolmogorov-Smirnov and Cramér-von Mises statistical tests, of,$T_n = f\{Q_n(.)\}$ with *f(.)* represents the functionals for these two statistical tests, as follows:

$$T_{1n} = \sqrt{n} \quad \sup_{t\epsilon T} |Q_n(t)| \ T_{2n} = \sqrt{n} \quad \int_{t\epsilon T} |Q_n(t)|\, dt$$

These statistics and the associated theory of limits provide a natural basis for testing the null hypothesis. Many tests can be formulated using variants of the proposed tests. Note that inference for a point estimate for a fixed treatment level can be considered as a special case of uniform inference with r(t) $=q_0$ and $T = t$. Alejo et al, (2018) [5] show that simple hypothesis tests for fixed t can be based on Wald statistics. For uniform inference of QCTE, we consider the following general null hypothesis:

$$H_0: \Delta_{\tau 0}(t, t+\delta) - s(t) = 0 \text{ with } t \in T$$

uniformly, where δ is a fixed treatment increment, *s(t)* is assumed to be known (continuous in *t over T),* and s $\in \ell^{\infty}$ *(T).* Inference is carried uniformly over the set of treatment levels, *T*. The basic inference process is

$$D_n(t) \coloneqq \hat{\Delta}_\tau(t, t+\delta) - s(t) \text{ with} t \in T \tag{7}$$

As before, we consider Kolmogorov-Smirnov and Cramer-von Mises test statistics, $T_n = f\{D_n(.)\}$, with *f(.)* representing the functionals for these two statistical tests, as follows:

$$T_{3n} = \sqrt{n} \quad \sup_{t \epsilon T} |D_n(t)| \quad T_{4n} = \sqrt{n} \quad \int_{t \epsilon T} |D_n(t)|\, dt$$

Note that point inference for two different treatment values, say *t* and *t',* can be stated as a particular case with $\delta = t'\text{-}t$, *r(t)* $=\Delta_0$, and $T = t$. Again, the Wald statistic is valid in this particular case. In practice, the procedure is implemented in a discretized subset, most conveniently on intervals of equal size, $T = [t_1, \dots \dots, t_m] t_1 < - - - < t_m$. The weak limits of T_{1n}, T_{2n}, T_{3n} and T_{4n} are functionals of Gaussian processes, and the estimation of their covariance kernel is difficult to compute. Therefore, to make practical inference, Alejo et al., (2018) [5] suggest using simple bootstrap techniques to approximate the limiting distribution (Alejo et al., 2020) [4].

3.3. Data

To achieve our objective, the data comes from the survey carried out in 2014 as part of the International Development Research Centre (IDRC) project on the determinants of business performance in sub-Saharan Africa. From this, a sample of 639 Cameroonian companies was extracted, of which only 162 invested in R&D.

3.3.1. Outcome and Treatment Variables

The aim is to analyse the effect of R&D on company performance. Performance is measured firstly by value added and secondly by net profit. The logarithmic transformation is not applied to these variables to avoid removing several observations with negative values (D'Attoma & Pacei, 2016) [22]. Value added measures the difference between the value of production and intermediate consumption, plus the trade margin (Tsambou & Fomba Kamga, 2021) [68]. It is used in this study because it measures a company's gross wealth creation and reflects its long-term performance (Dai et al., 2019) [23]. Net Profit is used because it is the short-term performance of firms and can be affected by firms' current operations or by accounting treatment alone (Dai et al., 2019) [23]. In this article, the treatment of effects concerns the allocation of R&D expenditure by firms. Thus, only companies that have carried out R&D expenditure are taken into account. They are then assigned to four treatment groups with different levels of R&D spending, based on the work of D'Attoma & Pacei (2016) [22] and L äpple & Thorne (2019) [43].

3.3.2. Covariables

Fundamentally, the aim is to identify and control for confounding variables. The general rule is to include all covariates that have an association with treatment and outcome variables (Bekele et al., 2018) [13]. However, Brookhart et al., (2006) [17] propose that including covariates that have an association with an outcome variable independently of their association with a treatment variable is useful for reducing the variance of the estimated treatment effect. Given all the concerns associated with covariate selection, Garrido et al. [28] suggest that covariate selection should be guided by trade-offs between the effects of variables on potential bias and efficacy [13]. In view of the above, the cofactors selected in this study come from empirical work on the determinants of R&D [48], on the effect of R&D on firm performance [50] and on other determinants of firm performance (Tsambou & Fomba Kamga, 2023) [67]. The following factors were considered: company size, age, foreign ownership, exports, manager experience, region of operation, competition and sector of activity. Hence the table below:

Table 1. *Description of variables.*

Variables	Description	Signs
Result variable		
Performance	Added value Net profit	
Treatment variable		

Variables	Description	Signs
R&D	R&D expenditure + cost of experimental R&D + cost of acquiring R&D services + cost of machinery for technological innovation + cost of acquiring external technology software + cost of introducing technological innovations + cost of training staff in innovation and ICT + investment in ICT and technological innovation + other costs)	+/-
Covariates		
Company size	Number of company employees	
Age of the company	Number of years in business	
Export	1 if the company exports its goods and 0 otherwise	
Foreign participation	1 if the foreign shareholding is ≥50%.	
Manager experience	1 if the manager has experience and 0 otherwise	+/-
Region	1 if Bafoussam, 2 if Yaoundé and 3 if Douala	
Competition	1 if the company is facing competition and 0 otherwise	
Sectors of activity	1 for primary; 2 for secondary and 3 for tertiary	

Source: authors, based on literature

Descriptive statistics

Table 2. *Descriptive statistics.*

Variables	Total mean	Group 1 [1, 160] mean	Group 2 [160, 800] mean	Group 3 [800, 8000] mean	Group 4 [8000, 700000] mean
Added value	2912972	1283131	1221013	1038444	8192344
Profit	917857.4	191850.1	255506.2	389474.3	2869308
R&D	22463.76	53.87805	461.561	3126.525	87323.36
Company size	109.3086	30.09756	25.92683	63.975	321.3
Age of the company	15.3986	11.54136	10.10234	18.32483	21.85472
Foreign participation	.191358	.1707317	.0487805	.15	.4
Export	.2283951	.2439024	.0731707	.3	.3
Experience manager	.5864198	.4390244	.5853659	.675	.65
Locations					
Bafoussam	12	4	2	5	1
Yaoundé	65	15	20	17	13
Douala	85	22	19	18	26
Competition	.8950617	.902439	.9512195	..9	.825
Sectors of activity					

Variables	Total	Group 1 [1, 160]	Group 2 [160, 800]	Group 3 [800, 8000]	Group 4 [8000, 700000]
	mean	mean	mean	mean	mean
Primary	5	3	00	2	00
Secondary	49	15	13	11	10
Tertiary	108	23	28	27	30
Number of observations	162	41	41	40	40

Source: authors using Stata 16 software

The previous table shows that: all the companies whose R&D expenditure is between 8,000 and 700,000 have a higher average added value than the lower brackets. This phenomenon can also be observed for profits, which increase monotonically with the increasing level of R&D expenditure. This group is dominant in terms of average R&D expenditure, size, age and foreign participation, but less competitive than other companies at other R&D levels. This can be explained by the fact that this group is made up of large companies with greater technological financing capacity. They are also largely service companies.

4. Presentation and Analysis of Empirical Results

The results of the balancing test are a prerequisite for validating the use of GPS and the dose-response function.

4.1. Balancing Test for the Characteristics of the Generalised Propensity Score

In order to implement the test of the balancing property, we first compare the means of the covariates before treatment at four different levels of R&D expenditure. Based on the distribution of R&D expenditure, the treatment interval is defined as follows: $[1-160];]160-800];]\ 800-8000]$ and $]8000-700000]$ for all companies. The difference for each covariate is obtained by comparing the observations in one R&D interval with the other observations in the other three intervals. To do this, the results of the t-test for equality of means are presented in Table 3 below. For example, the first row of the table below compares the average size of companies whose R&D expenditure is less than 160 thousand CFA francs with that of other companies whose R&D expenditure is greater than 160 thousand CFA francs. In fact, the result indicates that companies with R&D expenditure of less than 160 thousand CFA francs have an average 1.55 chance of having an average size. The results of the t-tests of equality of means after adjustment of the GPS are presented in the same table. To obtain the statistics, GPS is estimated at the median level of R&D expenditure and then separated into five quantiles [45]. Within each quantile, differences are calculated by comparing the means of the pre-treatment covariates in that quantile with those of the out-of-quantile covariates. Generally speaking, the results in Table 3 show that after GPS adjustment, the differences between the pre-treatment covariates are attenuated. Thus, the balancing property is satisfied at the 1% significance level.

Table 3. *Characteristic balancing test.*

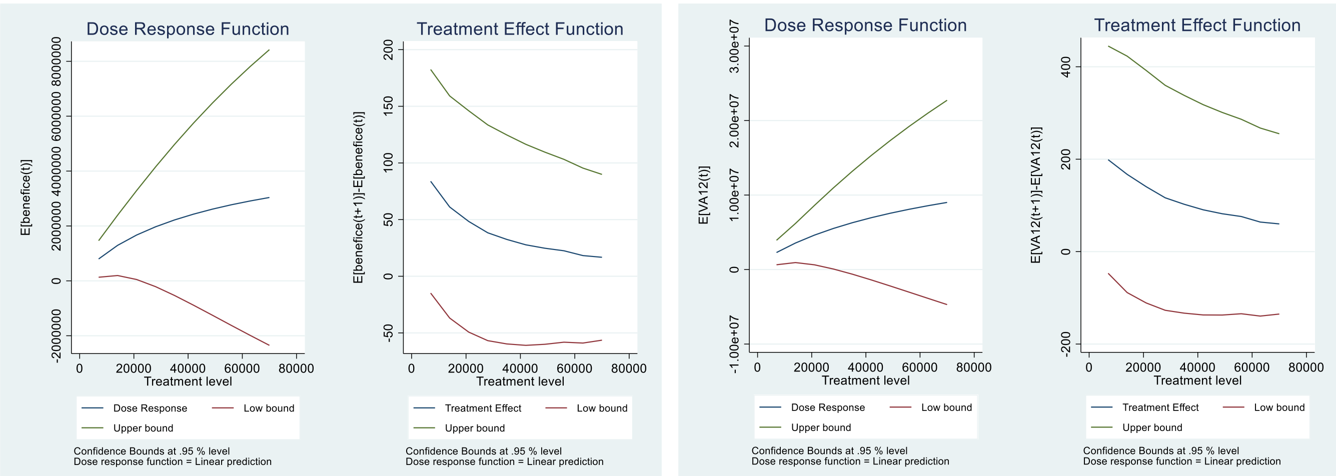
	Before adjustment				After adjustment			
R&D	Group 1 [1, 160]	Group 2 [160, 800]	Group 3 [800, 8000]	Group 4 [8000, 700000]	Group 1 [1, 160]	Group 2 [160, 800]	Group 3 [800, 8000]	Group 4 [8000, 700000]
Company size	1.5535	1.6366	0.8701	-4.2859	.93579	1.0125	.84166	-2.5889
Age of the company	2.2738	3.0376	-1.6576	-3.6141	.36519	1.42	-1.4049	-.74647
Foreign participation	0.3863	2.7302	0.7629	-4.0320	-1.0383	1.4065	1.0833	-2.1803
Export	-0.2721	2.7879	-1.2413	-1.2413	-1.3183	2.0533	-1.1028	-.99559
Manager experience	2.2380	0.0158	-1.3097	-0.9376	.23978	-1.4948	-.99922	-.39927
Region	0.1357	0.4214	1.4559	-2.0336	-.4858	.09186	1.2087	-.26706

R&D	Before adjustment				After adjustment			
	Group 1 [1, 160]	Group 2 [160, 800]	Group 3 [800, 8000]	Group 4 [8000, 700000]	Group 1 [1, 160]	Group 2 [160, 800]	Group 3 [800, 8000]	Group 4 [8000, 700000]
Competition	-0.1773	-1.3569	-0.1167	1.6701	-.10187	-1.211	-.47105	.3674
Sectors of activity	2.0381	-0.6415	0.1445	-1.5385	-.14506	-1.5779	-.12832	.08821

Source: authors using Stata 14 software

4.2. Estimated Results

The estimated coefficients do not provide any direct causal interpretation; however, they are used to estimate the dose-response function [38]. A more important interpretation of the results is represented by the dose-response function estimated according to equations (3) and (4). The dose-response function is calculated on average for each level of R&D expenditure and offers a direct interpretation of the treatment effect of R&D expenditure on profit and value added, which are the performance measurement indicators in this work. The dose-response function and the marginal effect are presented in figure 1 below. The dose-response functions show respectively the predicted profit and value added as a function of the pre-treatment covariates at each level of R&D expenditure. The solid lines represent respectively the annual profit and value added predicted by R&D expenditure. The dotted lines indicate the 95% confidence interval (CI) with 100 bootstrap replications. The marginal effect function shows the effect of each level of R&D expenditure on profit and value added respectively. Similarly, the dotted lines in the graph indicate the confidence limits at the 95% level with 100 bootstrap iterations.



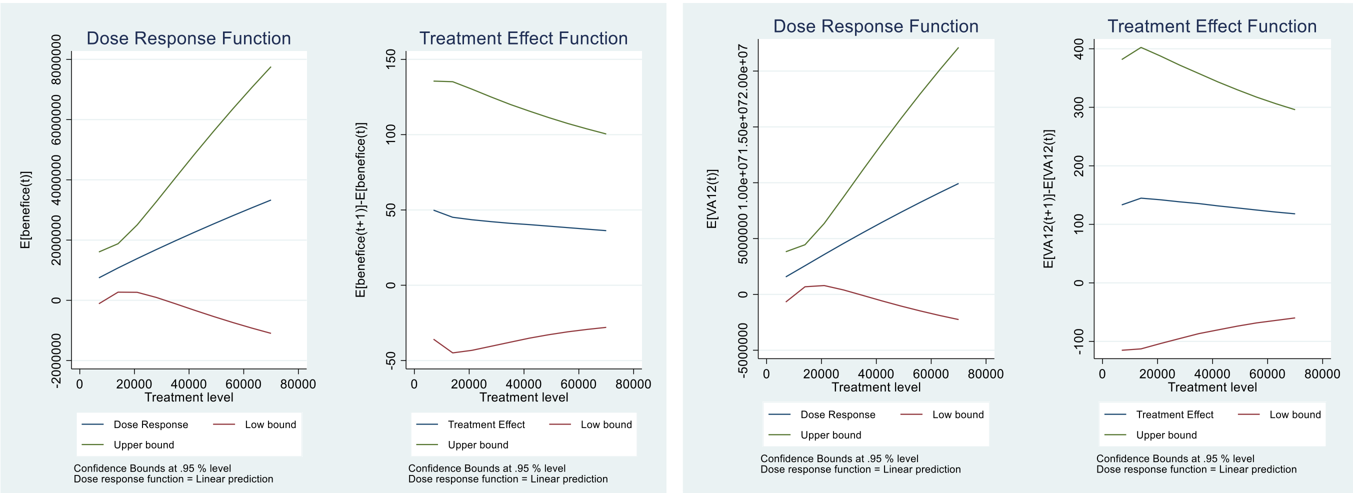
Source: authors using Stata 14 software

Figure 1. *Dose-response and marginal effect functions.*

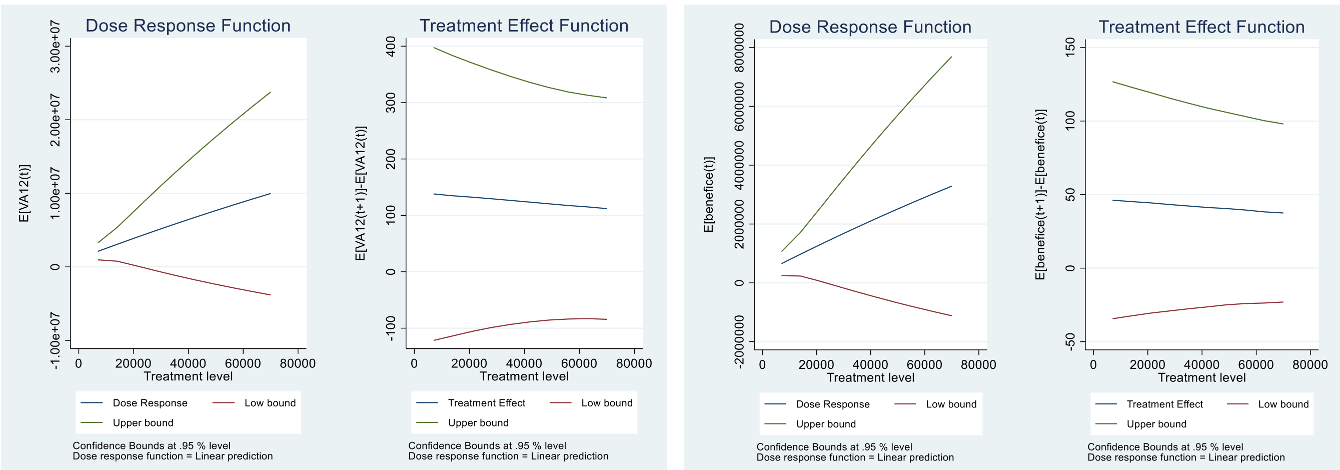
The dose-response functions do not differ in terms of monotonicity, magnitude or shape whatever the performance indicator. The dose-response functions start at zero and then take on the shape of increasing curves as R&D expenditure increases. This phenomenon becomes more pronounced when R&D expenditure exceeds almost CFAF 10,000. This means that annual net profit and annual value added increase monotonically with increasing R&D expenditure. This result was also found by Dai et al., [23] and by Yeh et al., [74]. The marginal treatment effect function shows the rate of change at each level of R&D expenditure. Thus, the continuous blue curves show that the marginal annual profit and the marginal value added, despite their decrease, do not reach the zero point. Furthermore, it should be noted that the CI of the marginal treatment effect function starts at almost 100 above zero for profit and at 200 for value added. This means that the marginal treatment effect is significant above the zero point. This implies that the increases in profit and value added linked to the increase in R&D expenditure beyond this point are more significant. This result seems to indicate that the marginal effect of treatment is significant beyond the zero point. This means that the marginal treatment effect of any R&D investment has a positive significant effect on the performance indicators of annual net profit and annual value added. This result was also found by Andrade et al. [7] and Mboe Bobo et al. [49]. And it means that R&D activities confer a temporary monopoly on the companies that adopt them. This is either due to the competitive advantage of the companies or to the externalities of the R&D activity [34, 35].

Robustness analysis

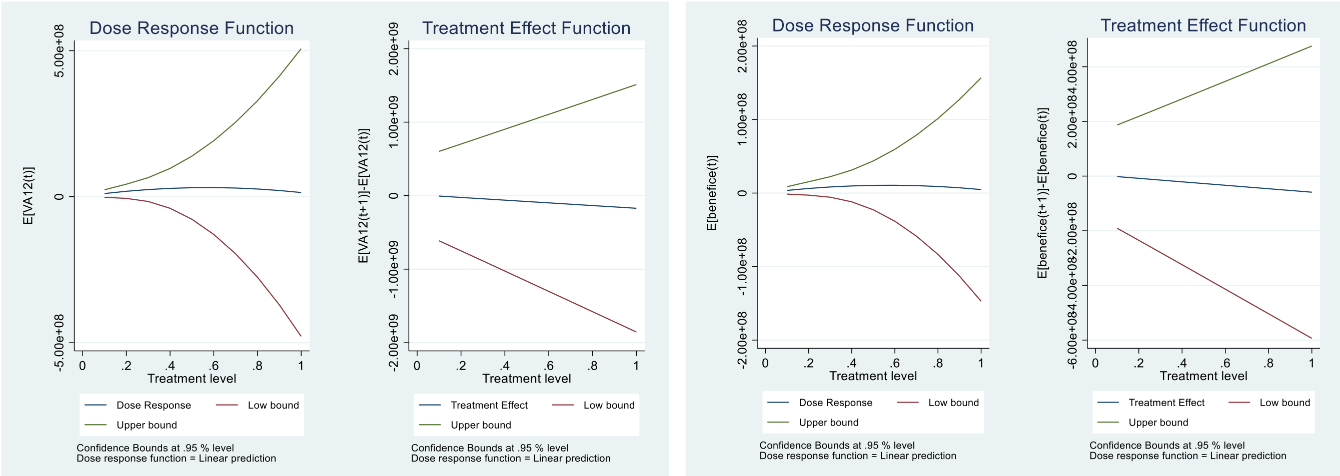
As a robustness check, the dose-response functions were estimated using the generalised linear approach (gamma distribution, negative binomial and fractional logit) and quantiles. They are presented in Figures 2 and 3 respectively below. The results are similar to those in Figure 1. The estimates of annual profit and value added in the dose-response function are estimates of the volume that companies would have achieved with the actual level of R&D spending. The quantile approach also confirms the cheekiness of the dose-response function in Figure 1, whatever the quantile (0.75 and 0.95), since quantiles less than or equal to 50% lead to zero results [4]. All this shows that our results are good.



Gamma



Negative binomial

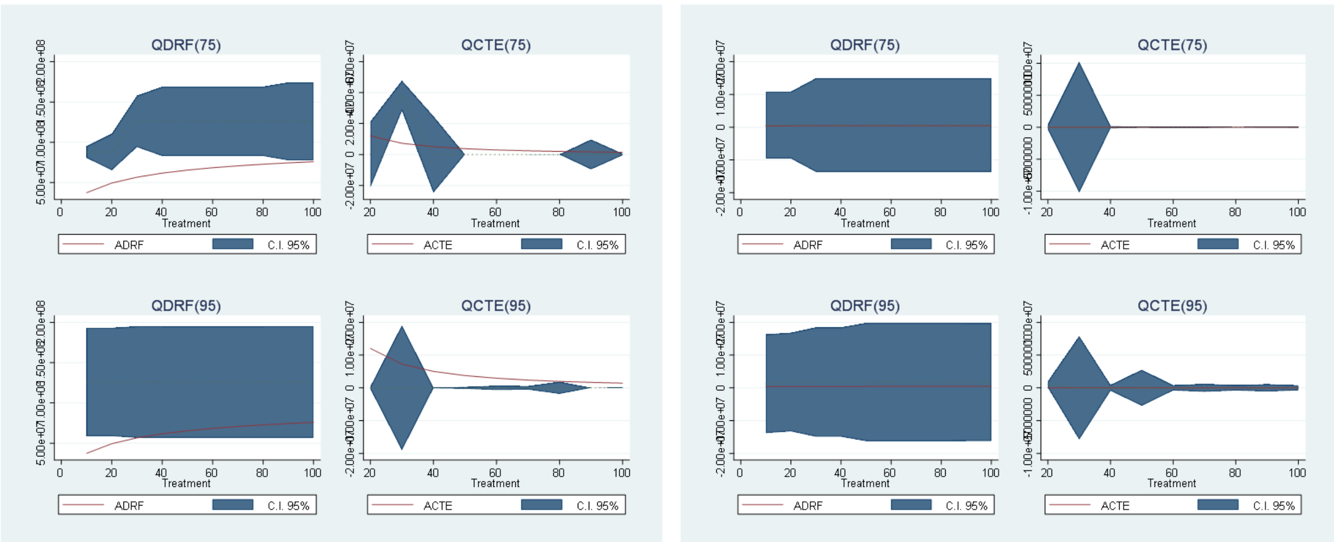


Fractional logit

Source: authors using Stata 14 software

***Figure 2**. The generalised linear approach.*

Added value **Profit**



Source: authors using Stata 14 software

***Figure 3**. The quantile approach.*

5. Conclusion

The objective of this study is to analyse the effect of R&D expenditure on the performance of companies in Cameroon. To this end, the generalised propensity score method is applied. The estimated dose-response function explains the relationship between R&D expenditure and performance indicators such as profit and value added of companies in Cameroon. Overall, the increase in R&D spending translates into a slight increase in company profits and value added. The results of this analysis are useful to managers and business owners for business decisions and decisions on the allocation of R&D expenditure. Thus, companies that invest in R&D activities in Cameroon stimulate their innovations and develop their capacity to absorb the externalities of R&D activities carried out by other companies. However, due to the lack of data, we did not analyse the moderating effect of advertising. Consequently, this method could be the subject of future research in other sectors of activity or in other commercial decision-making contexts.

These results show that the Cameroonian State should stimulate R&D within companies to enable them to bring themselves up to standard in order to face up to the fierce competition from competitors' products so that, in the long term, they can play an effective role in the country's development process. The State must therefore: Promote the development of the industrial sector, which will use and experiment with the results of research; intensify the partnership between companies and universities by setting up a technology watch unit in each university, which will enable these companies to use the results of research carried out in the universities; grant subsidies to companies interested in research.

Abbreviations

R&D	Research and Development
GPS	Generalized Propensity Score

Author Contributions

Mboe Bobo Mathurin Patrick is the sole author. The author read and approved the final manuscript.

Conflicts of Interest

The author declares no conflicts of interest.

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