

Cooperation and firm's capacity to innovation: Evidence from Cameroun

Pilag Kakeu Charles Bertin*, Kouhomou Clémence Zite, Tsakou Geoges Nazel

Faculty of Economics Sciences and Management, University of Dschang, Cameroun

ARTICLE INFO

Article history

Accepted 01 July 2020
Online release 17 July 2020

Keywords

Innovation, Cooperation
Externalities, SMEs
Private R&D, social R&D

*Corresponding Author

Pilag Kakeu Charles Bertin
Email: pilagbertin@yahoo.com

ABSTRACT

Innovation is the core element of economic growth and sustainable development. While there is emerging literature showing that cooperation is a vector of innovation, very little is known in the context of developing countries and particularly in the context of Cameroon, where there is existing enormous potentiality of innovation and economic growth. Therefore, this study aims to evaluate the effect of cooperation on firms' capacity to innovation. The empirical analysis focuses on the unobserved heterogeneity of externalities. The data analysis is based on a sample of 640 companies. The estimation method is a probit with selection from the analytical framework proposed by Heckman in 1979. The estimation is performed in two steps using the maximum likelihood estimator. The results revealed the existence of unobserved elements, due to cooperation, that reinforce the innovation capacity of firms. More specifically, the findings seem to suggest that the social benefits of R&D outweigh the private benefits, which is in line with external studies. To this end, innovation promotion policies should be oriented towards the promotion or intensification of cooperation in innovation. Future studies must take this into account.

INTRODUCTION

Innovation is the best way enabling economies to become emergent and allow firms to compete successfully in global markets. It is the process by which solutions are found to societal and economic challenges (Schumpeter, 1934; Druker, 1995; OECD, 2005). Indeed, during the numerous economics and financial, innovation has allowed many economies to be resilient (Filippetti and Archibugi 2011; Paunov 2012; Cruz-Castro et al. 2018), with a vision often oriented towards the creation of new jobs, the production of new goods and services, and the improvement of productivity (Mohnen and Hall, 2013; Morris, 2018; Cefis and Ciccarelli, 2005; Johansson and Löf, 2010; Hall and Bagchi-Sen, 2002; Geroski et al., 1993). Thus, the innovatory capacity of Cameroon is a critical factor in overcoming the negative effects of the VIDOC-19 pandemic and the way to reduce poverty as articulated under the United Nations Sustainable Development Goal (SDG1 and SDG9) (UN, 2015; Tomich et al., 2019). Thus it is especially important to find out what components of an R&D system are most decisive as engines of innovation and what are the factors determining systems' innovatory capacity (Buesa et al., 2010).

It is from this perspective that much researches has been made in recent years, giving rise to an abundance of theoretical and empirical literature. However, while most of these studies highlight a set of factors improving innovatory capacity, such as the human capital; size and distribution of innovatory firms; the role of universities and the

Public Administration; the degree of sophistication of demand; the financial system (availability of investment capital); and the R&D policies; (Buesa et al., 2010; Mongo, 2013; Mairesse and Mohnen, 2010), one unresolved issue in the literature concerns the role of cooperation on firm innovativeness. For example, many works shown that, the cooperation in innovation can have both positive and negative effects on innovation, making it difficult to determine its overall impact (Kim and Lui, 2015). Other studies note that the opportunistic behaviour of agents involved in the production and diffusion of knowledge tend to further complicate the understanding of the relationship between cooperation and innovativeness (Pisano, 1997; Das and Teng, 2000). All this shows that the debates concerning the role of collaboration on innovativeness still run. Yet, when it is mastered, cooperation can be a vector of innovation through the sharing of knowledge and skills. A firm's capacity to create new knowledge is critical for innovation activities. However, a firm alone cannot access the full critical mass of resources needed for innovation and must turn to external partners (Chesbrough, 2003). In this way, cooperation could allow a firm to benefit from the spillover effects of knowledge produced by other firms (Czarnitzki and Kraft, 2011; Vahter et al., 2011). In other words, cooperation gives firms access to knowledge that they could not have created on their own (Arrow, 1962). Thus, the potential of knowledge externalities that emerges queries the relevance of current innovation policies that are mainly oriented towards promoting private R&D, and suggests that policies to promote innovation should be oriented

towards intensifying cooperation in innovation. Moreover, the knowledge externalities resulting from cooperation show that the social benefits of research would potentially exceed the sum of the private benefits. Thus, any public intervention aimed at stimulating innovation should encourage innovation strategies that involve knowledge and skills exchange, since the decision to encourage innovation based on purely individual logics could lead to socially sub-optimal levels of research (Roper et al., 2013).

However, while there is emerging literature showing that cooperation is a vector of innovation, very little is known in the context of developing countries and particularly in the context of Cameroon, where there is enormous potentiality of innovation. This situation requires empirical research. Therefore, this paper attempts to fill this gap in the literature with the main objective of empirically assessing the effect of cooperation on the capacity of firms to innovate. More specifically, our article is a continuation of the work that analyzes the determinants of innovation by highlighting the predominant role of cooperation. Our contribution is to propose a new framework for the analysis of knowledge externalities based on micro-data. Indeed, while the idea of cooperation in innovation seems particularly attractive, its estimation raises a number of conceptual and econometric difficulties that the literature has not yet resolved. These include the problems of the proxy of cooperation and the problems of the endogeneity of this proxy.

The remainder of this paper focuses on three sections. In the second section, we present the methodological approach by specifying the data source, the sampling and the specification of empirical models. Then, we present in the third section the main results and finally the conclusion in the fourth section.

MATERIALS AND METHODS

Micro-data

Our empirical analysis is based on data from the survey on the determinants of firm performance in francophone sub-Saharan Africa: the cases of Cameroon, Côte d'Ivoire and Senegal (Chameni and Fomba, 2015), collected over the period 2014 with the support of the International Development Research Centre (IDRC). The Cameroonian data of particular interest to us relate to a sample of 640 enterprises (Chameni and Fomba, 2015).

However, the article deliberately remains focused on describing the interactive process of innovation. This choice is made in order to describe the process knowledge transfer and more specifically the way in which firms collaborate in innovation. In order to explicitly take the role of enterprises in the collaborative process of innovation, one of the questions asked to the heads of enterprises was: "During the last two years, have you cooperated with other enterprises or organizations in your innovation activities?". The observation in Table 1 reveals that slightly more than 68% of the enterprises surveyed acknowledge having cooperated with at least one external actor.

With regard to innovation capacity, we note that Cameroonian enterprises are relatively interested in the issue of innovation insofar as a little more than 2/3 acknowledged having innovated during the survey period (Chameni and Fomba, 2015. chapter 4). However, when we consider the different forms of innovation (OECD, 2005), we note that commercial innovations are the forms of innovation most developed by enterprises, followed by organizational innovations (Table 1). This leads us to question the causal link between cooperation and the different forms of innovation.

Empirical strategy

Our empirical strategy is based on the estimation of a knowledge production function in which the explained variable is innovation capacity (Créponet al., 1998; Love et al., 2011). As explanatory variables, we introduce cooperation in innovation as well as other standard determinants of innovation from the literature (Mongo, 2013; Mairesse and Mohnen, 2010). For variables dependent on the production function of innovation, we use four innovation indicators: product; process; organization; and marketing. These are dichotomous variables that have been tested and validated by the OECD's Oslo Manual (OECD, 2005). In our view, and compared to previous studies, these variables measure innovation more accurately than the qualitative variables of patents and R&D expenditure.

However, estimating the effects of cooperation raises a number of conceptual and econometric difficulties that need to be addressed. Conceptually, a major issue is whether cooperation can be considered as valid proxies for capturing knowledge externalities. Specifically, the question is whether the intensity of cooperation between firms can be

considered as an indicator of externality or whether this indicator only represents simple market transactions. Indeed, it cannot be concluded in a simple way that the cooperation indicator captures only simple market transactions, or that this indicator actually incorporates information on externalities, or both, for the simple reason that these indicators do not reflect the prices paid for the transfer of knowledge (Roper et al., 2013). It is therefore generally not possible to determine from the dichotomous responses which of these two situations is taken into account by the standard cooperation indicators. The problem of the endogeneity of these indicators is therefore crucial. In this paper, and base on previous words (Roper et al., 2013), we assume that the cooperation variable captures either simple market-based transactions, or externalities, or both.

Econometrically, the problem of estimating the effects of cooperation has been examined from the perspective of endogeneity problems by Manski (1995), Angrist and Pischke (2009) and Bloom et al (2012). The key problem is the potential endogeneity of cooperation and unobserved heterogeneity, which can affect the results of the econometric analysis and their interpretations. Indeed, it is not obvious to say that the coefficient corresponding to cooperation in an innovation model shows the effect of real externalities. Nor can it be said that more innovative firms are simply lucky enough to be in sectors that are more open to cooperation or are simply those that cooperate the most. Some unobserved variables may determine both the firm's ability to cooperate and its capacity to innovate. In particular, cooperation itself may be a linear function of a set of variables such as the characteristics of the manager and those of the firm (Roper et al., 2013). Such hazards deserve to be taken into account in the estimation process.

We contribute to the methodological plan by using an approach derived from the analytical framework proposed by Heckman (1979) in which the equation of interest is of the binary type. Such an analysis allows us to correct for selection and endogeneity bias (Mong0, 2013). The model is built on the idea that the probability that firm i engages in innovation activity is assumed to depend on a linear combination of explanatory variables relating to the characteristics of the firm, the manager and the industry.

These theoretical considerations lead us to specify the following structural form of the innovation function:

$$inno_{-i} = \beta_0 + \beta_1 coop_{-i} + \beta_2 X_{-i} + \varepsilon_i \quad (1)$$

where $inno_{-i}$ is an innovation indicator. It is a latent variable, to which is associated any outcome variable that takes 1 if the firm has innovated and 0 if not. The index i is for the firm. $coop_{-i}$ is the cooperation indicator that captures externalities. It is a binary variable that takes 1 if firm cooperates in innovation and 0 if not. The variable X_{-i} is a vector of standard innovation variables, including internal R&D, firm size, industry and age of the firm. ε_i is the error term that follows a normal law depending on whether one is in a probit or a logistic law depending on whether one is in a logistic model. The estimation of β_1 would give the effect of cooperation on innovation capacity. However, as noted above, it is possible that cooperation is enhanced by managerial capabilities, sectoral characteristics, gender considerations, human capital, and other unobserved characteristics, thus accentuating the issue of endogeneity of this variable. This leads us to specify the reduced form of collaboration as follows:

$$Coop_{-i} = \gamma_0 + \gamma_1 Z_{-i} + \mu_i \quad (2)$$

where Z_{-i} is a vector of control variables that takes into account the characteristics of the manager including gender, education, experience and other institutional characteristics, etc. μ_i is an error term. γ_1 is the vector of parameters to be estimated. In order to take into account the endogeneity problem, the two equations can be estimated simultaneously or in two steps. Following Heckman, equation (2) allows to correct the selection bias of the estimated parameters. The correction factor derived from equation (2), the inverse of the Mills ratio, is introduced into equation (1) as a regressor, allowing us to write equation (3) :

$$inno_{-i} = \pi_0 + \pi_1 coop_{-i} + \pi_2 X_{-i} + \pi_3 Millsinvers_i + \rho_i \quad (3)$$

The variable $Millsinvers_i$ represents the ratio of chance, which Heckman (1979) has called the inverse Mills ratio. It is estimated from the selection equation and then introduced into the third equation as a regressor. ρ_i is the new error term. π_i is the new parameter to be estimated. The estimation is performed in two steps using the maximum likelihood estimator.

RESULTS AND DISCUSSION

Some descriptive statics

Table 1 provides descriptive statistics on all variables. Concerning the explanatory variables, empirical observation shows that very few firms report investing in R&D activities. However, this low investment can be compensated by externalities, i.e. knowledge produced externally, in particular acquired through cooperation. This is justified by the fact that 68.7% of companies acknowledge having cooperated. As far as concerned the typology of companies, it can be seen that medium-sized companies are in the majority in our sample. They account for almost 70% of the sample, compared with almost 20% of large companies. Considering the heavy investment in R&D and the relatively limited resources of SMEs, one can understand the

low propensity to invest in in-house R&D. One randomly selected company in the sample is 11 years old. This trend reflects a certain experience of managers, and may also increase their likelihood of innovation.

Moreover, the presence of a firm within a multinational corporation represents a potentially important channel for international knowledge transfer (Lipsey, 2002) and can therefore affect innovation performance. Indeed, SMEs that are part of large international groups are likely to benefit from skills transfer. In addition, foreign-owned firms may be more efficient in innovation, through access to resources and knowledge within business networks. Our sample shows that just over 30% of the companies surveyed belong to international groups.

Table 1: Descriptive statistics on all variables

Variables		Mean	Std. Dev.
Dependent variables			
Product innovation	yes	0.475	0.499
Business Innovation	yes	0.564	0.499
Process innovation	yes	0.46	0.495
Organizational innovation	yes	0.497	0.500
Endogenous variables			
Cooperation (external R&D)	yes	0.686	0.389
Innovation standard covariates (X_i)			
Internal R&D	no	0.917	0.276
Company size	yes	0.697	0.459
Age of the company		110.335	110.39
Belonging to a group of companies	yes	330.047	210.41
Medium Technology Sector	yes	0.659	0.475
High Technology Sector	yes	0.316	0.491
Control variables (Z_i)			
Gender (Man)	yes	0.728	0.445
Primaryeducation	yes	0.179	0.383
Secondaryeducation	yes	0.463	0.499
Highereducation	yes	0.338	0.474
Havingexperience	yes	1.556	1.038
Lack of qualified personnel	yes	1.909	0.4123
Lack of internalfunding	yes	1.467	0.580
Derived variable			
Inverse Mills Ratio		0.849	0.255

Source : Survey

In addition, we include a human capital indicator. This is the share of employees in each company that have a certain level of education (Freel, 2005). Like R&D, this variable can also capture the absorptive

capacity of the firm. Thus, while empirical observation of the data shows that most of the heads of the firms surveyed are male, most of them have a secondary level of education. Our data show the

predominance of the medium technology sector with 65% of respondents. The results of the econometric estimations are presented in the following subparagraph.

Empirical results

In order to account for the endogeneity of our measure of externalities, which is cooperation, we have adopted Heckman's two-step approach. First, we estimated a selection equation, based on some control variables, and introduced linear predictions into the innovation equation. Thus, Table 2 highlights the results of our selection equation. Indeed, the observation of the econometric results shows that the selection model is globally significant at the 1% threshold.

Indeed, most of the control variables introduced into the model are statistically significant and show the signs expected for such an analysis, even if their interpretation does not seem interesting now. This estimation allowed us to derive the Mills ratio, which represents the probability that co-operation represents not only simple market transactions, but an important vector of knowledge transfer as well as some elements of unobserved heterogeneity.

Table 2: Estimation of the selection equation

Variables explicative	Coop
Gender	0,236* (0,147)
Educationallevel	0,242*** (0,0938)
Havingexperience	0,0603 (0,0615)
Internal RD	-0,674*** (0,209)
Lack of qualified personnel	-0,697*** (0,189)
Lack of internal funding	-0,238* (0,152)
Constant	1,454** (0,617)
Wald chi2(9)	56,01
Prob > chi2	0,0000
Pseudo R2	0,1516
Observations	579

Robust standard errors in parentheses *** p<0,01; ** p<0,05; * p<0,1

Table 3 summarizes the results of the estimation of knowledge externalities on innovation capacity. The first interesting result concerned the mills ratio. We can observe that, the Mills ratio shows a significant and positive effect for the four innovation models studied. These results indicate that, within firms, innovative capacity and cooperation are significantly and positively correlated with certain unobserved characteristics. These results are in line with the previous studies, who, by adopting an instrumental variable approach, find that research externalities strengthen the innovative capacity of firms.

Furthermore, we find as expected that the probability of innovation increases with the intensity of technological opportunities in the business environment (cooperation). However, this variable does not appear to be statistically significant in the case of product and process innovations, although a positive effect can be observed. This result can be explained by the fact that product and process innovations are part of the internal strategy of firms and do not require third parties to be made aware of them. These results are consistent with those of Kim and Liu (2015), showing that the effects of cooperation on innovation capacity may vary according to the forms of innovation.

With respect to the other variables introduced in the analysis, one would expect that the business group affiliation could affect the probability of innovations by facilitating access to information (Lipsey 2002). However, we arrive at a counter-intuitive result according to which, although the firm group variable appears to be positively correlated with innovative capacity, it is not significant for any form of innovation.

We have also included in our models the geographical location of companies. The results show a significant effect for product and process innovations. These results are consistent with Tojeiro-Rivero and Moreno (2019) studies showing that geographical proximity contributes to the emergence of innovations.

Table 3: Estimation of cooperation on innovation

	(1)	(2)	(3)	(4)
VARIABLES	Product	Business	Organizational	Process
Coop	0,0559 (0,146)	-0,307* (0,161)	-0,525*** (0,158)	0,130 (0,153)
Internal RD	0,249 (0,271)	-0,234 (0,274)	0,240 (0,288)	0,419* (0,284)
Age of the company	-0,192* (0,101)	-0,132 (0,104)	-0,113 (0,103)	-0,180* (0,109)
Size	-0,0177 (0,278)	0,217 (0,274)	0,676** (0,270)	0,336 (0,272)
Size 2	-0,0397 (0,131)	-0,0363 (0,134)	-0,259* (0,132)	-0,0950 (0,135)
High Technology Sector	0,215*** (0,0311)	0,148*** (0,0233)	0,109*** (0,0240)	0,219*** (0,0300)
Belonging to a group of companies	0,211 (0,208)	0,133 (0,199)	0,0159 (0,199)	0,175 (0,198)
Medium Technology Sector	0,0688 (0,0447)	0,0868** (0,0365)	0,0738** (0,0365)	0,0696 (0,0466)
Lambda (Mills ratio)	0,364* (0,228)	0,849*** (0,243)	0,797*** (0,234)	0,904*** (0,242)
Constant	-1,553*** (0,543)	-1,464** (0,571)	-2,136*** (0,604)	-3,425*** (0,621)
Observations	579	579	579	579

Robust standard errors in parentheses *** p<0,01; ** p<0,05; * p<0,1

CONCLUSION

The objective of this paper was to empirically analyze the effects of cooperation on innovation capacity. Using a probit model with selection, we find that our indicator of externalities positively influences the capacity of Cameroonian firms to innovate. More specifically, our findings seem to suggest that cooperation is the best way to share knowledge and improving innovation capacity. To this end, innovation promotion policies should be oriented towards the promotion or intensification of cooperation in innovation.

Nevertheless, these results should be interpreted with great caution, as there is no certainty that we have captured knowledge transfers. In addition, we analyze an indicator of externalities that does not take into account the prices paid for knowledge transfer. Thus, for coming studies ought to take in to consideration these limitations. Another limitation concern the indicator of innovation. Indeed, as we demonstrated in the case of regression analyses, there is a link between cooperation and the probability of innovation. However, our results are

not easily generalizable. Because we are working on microdata, which tends to cover our results with a veil of subjectivity. Furthermore, we measure innovation through qualitative variables, yet these indicators are likely to capture innovation with less objectivity, compared to patent data or R&D expenditures.

REFERENCES

- Angrist, J. & Pischke, J. (2009). *Mostly Harmless Econometrics. An Empiricist's Companion*, Princeton University Press, Princeton, New Jersey.
- Arrow, K., 1962. The economic consequences of learning by doing. *Rev. Econ. Stud.*, 29(3):155–173.
- Bloom, N., Schankerman, M. & Van Reenen, J. (2012), Identifying technology spillovers and product market rivalry. *CEP Discus. paper*, 675 p.
- Buesa, M., Heijs, J. & Baumert, T. (2010). “The determinants of regional innovation in Europe: A combined factorial and regression knowledge production function approach”. *Res. policy*, 39(6): 722-735.
- Cefis, E. & Ciccarelli, M. (2005). Profit Differentials and Innovation. *Econ. Innov. New Technol.*, 14 (1– 2), 43–61.

- Chameni Nembua, C. & Fomba Kamga, B. (2015) Rapport général de l'étude sur les déterminants de la performance des entreprises en Afrique subsaharienne francophone: cas du Cameroun, de la Cote d'Ivoire et du Sénégal; *rapport du Cameroun*.
- Chesbrough, H.W. (2003). Open innovation: The new imperative for creating and profiting from technology. *Harvard Business Press*.
- Crepon, B., Duguet, E. & Mairesse, J. (1998). Research, innovation and productivity: an econometric analysis at the firm level. *Econ. Innov. New Technol.*, 7: 115–158.
- Cruz-Castro, L., Holl, A., Rama, R. & Sanz Menéndez, L. (2018). Economic Crisis and Company R&D in Spain: Do Regional and Policy Factors Matter? *Ind. Innov.*, 25 (8): 729–751.
- Czarnitzki, D. & Kraft, K. (2011). Spillovers of innovation activities and their profitability. *Oxf. Econ. Pap.*, 64(2): 302–322.
- Das, T.K. & Teng, B.S. (2000). A resource-based theory of strategic alliances. *J. Manage.*, 26(1): 31-61.
- Drucker, P.F. (1995). *Management in a time of great change*. New York: Dutton.
- Filippetti, A. & Archibugi, D. (2011). “Innovation in Times of Crisis: National Systems of Innovation, Structure, and Demand.” *Res. Policy*, 40 (2): 179–192.
- Freel, M.S. (2005). Patterns of innovation and skills in small firms, *Technovation*, 25: 123–134.
- Geroski, P. (1995). What do we know about entry? *Int. J. Indust. Org.*, 13(4): 421–440.
- Hall, L. & Bagchi-Sen, S. (2002). A Study of R&D, Innovation, and Business Performance in the Canadian Biotechnology Industry. *Technovation*, 22, 231–244.
- Heckman, J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47: 153-162.
- Johansson, B. & Lööf, H. (2010). Innovation Strategy and Firm Performance what is the Long-Run Impact of Persistent R&D? Working Paper Series in Economics and Institutions of Innovation, 240, Royal Institute of Technology, CESIS, Centre of Excellence for Science and Innovation Studies.
- Kim, Y. & Lui, S.S. (2015). The impacts of external network and business group on innovation: Do the types of innovation matter? *J. Business Res.*, 68(9): 1964-1973.
- Lipsey, R.E. (2002). Home and Host Country Effects of FDI. *NBER Working Paper*, 9293.
- Love, J.H., Roper, S. & Vahter, P. (2011). Learning from Open Innovation. CSME Working Paper No. 112. Warwick Business School.
- Mairesse, J. & Mohnen P. (2010). “Using innovation surveys for econometric analysis”. In *Handbook of Eco. Innov.*, 2: 1129–1155.
- Manski, C. (1995). Identification Problems in the Social Sciences. Harvard University Press, Harvard, Massachusetts.
- Mohnen, P. & Hall, B.H. (2013). Innovation and Productivity: An Update. *Eurasian Business Rev.*, 3(1): 47–65.
- Mongo, M. (2013). Les déterminants de l'innovation : Une analyse comparative service/industrie à partir des formes d'innovation développées. *Rev. économie indust.* (143): 71–108.
- Morris, D.M. (2018). Innovation and Productivity Among Heterogeneous Firms. *Res. Policy*, 47: 1918–1932.
- OCDE (2005). Manuel d'Oslo: principes directeurs pour le recueil et l'interprétation des données sur l'innovation. OECD Publishing.
- Paunov, C. (2012). The Global Crisis and Firms' Investments in Innovation. *Res. Policy*, 41 (1): 24–35.
- Pisano, G.P. (1997). The development factory: unlocking the potential of process innovation. Harvard Business Press.
- Roper, S., Vahter, P. & Love, J.H. (2013). Externalities of openness in innovation, *Res. Policy*, 11 p.
- Schumpeter, J.A. (1934). *The theory of economic development*. Cambridge (Mass.): Harvard University Press.
- Tojeiro-Rivero, D. & Moreno, R. (2019). Technological cooperation, R&D outsourcing, and innovation performance at the firm level: The role of the regional context. *Res. Policy*, 48(7): 1798-1808.
- Tomich, T.P., Lidder, P., Coley, M., Gollin, D., Meinzen-Dick, R., Webb, P. & Carberry, P. (2019). Food and agricultural innovation pathways for prosperity. *Agri. Sys.*, 172, 1-15.
- UN (2015). Les objectifs de développement durable. Nations Unies.
- Vahter, P., Love, J.H. & Roper, S. (2011). Openness and Innovation Performance: Are Small Firms Different? *CSME Working Paper No.113*.