Human Capital, Innovation and Productivity in Colombian Enterprises: A Structural Approach using Instrumental Variables

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Abstract

In this paper we explore the R&D-innovation-productivity linkage for the Colombian manufacturing industry, paying special attention to the role of human capital. Using data from two firm-level surveys such as the Survey of Development and Technological Innovation (EDIT) and the Annual Manufacturing Survey, we extended the model of Crepon, Duget and Mairesse (hereafter CDM) due to Crepon *et al.* [1998] by including human capital at the investment decision stage. We implement an instrumental variable methodology to correct the potential endogeneity that may arise when including human capital into the model. Our results suggest that human capital has a causal effect on the research and development (R&D) investment decisions and the innovation behavior of the firm and, finally increasing the labor productivity of the firm. The conclusions of our work highlight the relevance of human capital in the CDM-type of literature and contrast with the relative little importance that this variable has received in this kind of models.

Key Words: Innovation, Productivity, Human Capital

JEL Classification: O30, J24.

1 Introduction

The literature on economic growth presents two fundamental alternatives to make the output of an economy grow: first, to put more inputs into the production process or, second, to find new ways to produce more output while keeping the amount of inputs fixed (Rosenberg [2004]). The Solow residual refers to the second alterntative as the portion of growth that cannot be explained by an increase of inputs (Solow [1956]). Started with Griliches [1980] an extensive literature has related this residual with technical change and innovation. In thise sense, innovation is crucial for long-term economic growth and is a strong factor explaining the competitive advantages of firms and differences in performance across companies, regions, and countries [Rouvinen, 2002; Rosenberg, 2004; Fagerberg, 2009]. Empirically, there is strong evidence from many countries on the economically significant effect of innovation on productivity, and the conclusions of numerous studies point out that innovation actually leads to better productivity performance ([Hall *et al.*, 2010; Hall, 2011]).

Having a better understanding of the innovation determinants is important because it leads to a better knowledge of what elements drive enterprises to perform innovation and to what extent these elements contribute to it. Human capital has been receiving special attention regarding its relationship with innovation in recent years [Busom & Vélez-Ospina, 2017]. In this study, we argue that human capital is essential for explaining innovation, in particular investments decisions on R&D activities, and there are solid reasons to believe that the relationship between human capital and innovation is strong [Crowley & McCann, 2018; Gallego *et al.*, 2015]. The literature highlights the well-known "skill-bias hypothesis" which postulates that technical change favors skilled over unskilled labor by increasing its relative productivity and, therefore, its relative demand (Piva & Vivarelli [2002]; Cohen & Levinthal [1989]). Another important reason supporting our argument is that human capital reduces implementation times and lowers adjustment costs due to individual and organizational capacity to use new technologies in better ways. It also enhances capital-skill complementarities, which helps lower adjustment costs. Better skills of the labor force lower the need for post-innovation human resource management practices and training; moreover, a more educated staff leads to higher absorptive capacity and the expected costs diminish due to a possible skill shortage (Piva & Vivarelli [2009]).

There is also economic theory supporting the linkage between human capital and productivity. According to economic growth theory, there are two mechanisms through which human capital impacts productivity: the level and the rate effects. The first stipulates that the stock of human capital has a direct impact on the level of output and, in the second, human capital affects the growth rate of output through innovation and diffusion of new technologies and, thus, technical change, which end up impacting total factor productivity (TFP). This arguments could well be translated into the context of industrial economics (De la Fuente & Ciccone [2003]; De la Fuente [2011]; Huergo & Moreno [2006]). Other studies that highlight the importance of human capital in productivity are presented by Castiglionesi & Ornaghi [2004] and Alba [1993].

This study mainly aims to go deeper into the understanding of the relationship between R&D investments, human capital, innovation, and productivity for Colombian enterprises in the manufacturing sector. Our work is based on the CDM structural model proposed by Crepon *et al.* [1998] and the adaptation presented by Crespi *et al.* [2016] for Latin American economies. Gallego *et al.* [2015] studied Colombian enterprises within a similar framework, including a modification for considering human capital within the model. This literature had omitted the possible endogeneity that could arise by adding human capital; in this study, we attempt to deal with this difficultiy through an instrumental variable (IV) approach. To the best of our knowledge, this is the first empirical work that tries to tackle the endogeneity of human capital in the relationship between R&D, innoavtion and productivity using the IV method within the framework of a CDM model, except for Czarnitzki & Delanote [2017] who implemented an IV approach at the CDM model in a context of public subsidies to R&D. Our preferred instruments are the lagged value of that we defined as exogenous human capital (i.e. the proportion of workers with technical or higher studies as a proportion of the total of employees without taking into account those who carry out R&D tasks) and the lagged value of that we defined as endogenous human capital (i.e. the number of workers carrying out R&D tasks as a percentage of the total number of workers). Our results suggest that human capital has a causal effect on the research and development (R&D) investment decisions and the innovation behavior of the firm and, finally increasing the labor productivity of the firm. The conclusions of our work highlight the relevance of human capital in the CDM-type of literature and contrast with the relative little importance that this variable has received in this kind of models.

The remainder of this study is organized as follows. Section 2 presents a review of the literature regarding human capital, R&D investments, innovation, and productivity, focusing on applications of the CDM model. Section 3 explain what datasets we use, and what variables we are going to work with. In section 4, we present a relatively detailed empirical approach including the modification we propose for the CDM model. The most important findings of our research are reported in section 5. Finally, in section 6, some conclusions are reported and further research recommendations are posed.

2 Literature review

The neoclassical growth model, based on the original work of Solow [1956], concluded among others that technological change is crucial for explaining economic growth. Today, knowledge, research, and innovation are widely recognized as powerful explanatory factors for competitiveness, economic performance, high standards of living, productivity, and welfare. Newer endogenous growth theories built upon the contributions presented by Romer [1986], [Lucas, 1988], Rebelo [1991] and others arose as possibles answer to the preceding dissatisfaction. One aspect worth mentioning regarding these perspectives is that they described human capital, as the engine of economic growth through knowledge and innovation Aghion *et al.* [2006].

The importance of human capital within the relationship of innovation and productivity is tangible. Grossman & Helpman [1993] showed that the skill composition of the labor force is a key factor determining the amount of innovation in the economy. Vinding [2006] explains that the technological element is crucial for the competitive advantage for individual firms, nations and the world as a whole. He argues that highly educated employees increase the stock of knowledge of the firms through the execution of their daily tasks. These employees also facilitate access to external networks of knowledge due to their relationships with other individuals with similar competencies outside the firm. In Vinding's study the author finds a positive correlation between the workers' education and the ability of the firm to innovate. Lopez-Garcia & Montero [2012] explain that a firm absorptive capacity is strongly related with its human capital. Moreover, skill composition of the workforce increase the probability of being innovative, not directly, but because it raises the capacity of a firm to benefit from external technological spillovers. Arvanitis *et al.* [2016] consider human capital as a driver of innovation performance. They test this postulate and find that human capital actually matters primarily for R&D activities and product innovation for the Swiss case.

The study of the link between R&D to innovation, and innovation to productivity at the empirical level entails various difficulties like the measure of knowledge capital and how to control for potential unobserved heterogeneity of firms at the moment to consider the innovation efforts, outcomes and measures of productivity, which became clear after several early important efforts such as those by Griliches [1980, 1994, 1998]; Jorgenson & Griliches [1967]; Gollop & Jorgenson [1979], and others. In 1998, Crepon, Duguet, and Mairesse proposed a structural model to deal with such problems. The CDM model is a very important development that enriched our understanding of the R&D-innovation-productivity relationship. The CDM model is and structural approach that extended the idea of a broad production function that includes knowledge creation (or innovation) as determinant (Griliches [1980]). The model is developed into three stages that consider, first, the investment decision on innovation or R&D activities and controlling by potential selection problems. At the second stage, the estimated amount of investments are included in a knowledge production function that relates R&D to innovation. Finally, the third stage is a extended production function that combines measures of traditional production factors, like capital and labor, and the new measure of technological change estimated by the innovative behavior of the firm from the second stage. The use of this model has expanded and, presently, there are studies applying this approach —or a modification of it— in many countries around the world (see Hall *et al.* [2010] for a review of the literature, and Lööf *et al.* [2017] for recent developments of the CDM model with a dynamic approach). For developing countries, the lack of reliable data has translated into less evidence Busom & Vélez-Ospina [2017]; however, as stated before, this type of empirical literature has recently begun to flourish. Although human capital has a very clear theoretical effect on innovation and productivity, it is surprising how little attention has been paid by many researchers using a CDM model (except by Gallego *et al.* [2015] and Crowley & McCann [2018]).

2.1 Applications of the CDM model in the literature

Lööf *et al.* [2017]; Mohnen & Hall [2013]; Hall [2011]; Cohen [2010]; Hall *et al.* [2010] present very enriching and detailed reviews of the literature on the relationship between R&D, innovation, and productivity. Internationally, for developed economies, there are multiple investigations tackling slightly different problems. In the case of The Netherlands, we can highlight the following studies: Belderbos *et al.* [2004] focused on R&D collaboration, differentiating four types of R&D partners (competitors, suppliers, customers, and universities) concluding that the cooperation between supplier and competitor has a significant impact on labor productivity growth; [Van Leeuwen & Klomp, 2006] focused their analysis on the relationship between innovation and multi-factor productivity growth, finding a rather strong support for the "absorptive capacity hypothesis"[1] The same result was obtained by Parisi *et al.* [2006] for the French economy; Polder *et al.* [2009] modified the CDM model to include Information Communication Technology (ICT) in their analysis and conclude that ICT is an important driver of innovation in both manufacturing and services.

[1]"The ability to exploit external knowledge is a critical component of innovative capabilities" Cohen & Levinthal [1990]

For French enterprises, Mairesse *et al.* [2005] studied the relationship between innovation and productivity, concentrating on the productivity elasticities of innovation and R&D. Along with the work of Duguet [2006], they emphasized the importance of data collection and its relevance for future studies; that is, measuring the innovation height is crucial for assessing the impact of spillovers on innovative output. Duguet [2006] found evidence supporting that only radical innovation significantly contributes to TFP growth. There is also some literature available for transition countries. In the case of China, Jefferson *et al.* [2006] used a variation of the CDM model to investigate firm-level R&D intensity, the process by which knowledge is produced, and the impact of innovation on firm performance. These researchers found that state-owned companies exhibit the lowest efficiency in knowledge production, although once new knowledge is acquired, these firms use innovations effectively, or sometimes even more so, than enterprises with different ownership structures. Masso & Vahter [2008] analyzed the Estonian economy and pointed out that the significance of process or product innovation is different across periods of time.

There is also some literature that concentrates on comparing different countries in terms of their innovation—productivity relationship at the firm level, although these comparisons are difficult largely due to the heterogeneity of the data across countries. Comparability is relevant to better understand the situation of a single economy and its relationship with its region and the world; in fact, one of the remaining challenges in this area is to harmonize surveys to make them truly internationally comparable [Lööf *et al.*, 2001; Mohnen & Therrien, 2005; Crespi & Zuniga, 2012]. For example, Griffith *et al.* [2006], analyzed four different economies from Western Europe and found the systems driving innovation and productivity in these economies to be very similar; at the same time, however, they also found differences in terms of the variation in productivity associated with innovative activities.

In this line some recent studies have focused their attention in developing countries. For example, Samargandi [2018] explores the role of core determinants of labor productivity, such as human capital and innovation, for Middle East and North African countries. They find that both of these variables foster labor productivity. In the same line, Crowley & McCann [2018] investigates the link between innovation and productivity for firms in transition economies, employing a variant of the CDM model and assessing if there are differences across sector type, manufacturing vs services. For Latin American countries Crespi *et al.* [2016] presents the strong relationship between R&D investments, innovation and productivity and Gallego *et al.* [2015] studied Colombian enterprises in the manufacturing and services sector considering the human capital as a determinant of the investment decision.

2.2 The role of human capital

Most of the studies mentioned above have not included human capital into their analysis, even though it has a clear and well documented interaction with both innovation and productivity. However, there are some research efforts that actually include indicators of human capital within a CDM model framework. For instance, comparisons between countries that consider some measures of human capital have been performed. Lööf *et al.* [2001] compared Nordic European countries and found positive and significant effect of human capital on productivity for Finland and Norway but not for Sweden. Raffo *et al.* [2008] compared six European and Latin American countries, three from Europe (France, Spain, and Switzerland) and three from Latin America (Argentina, Brazil, and Mexico), and found structural differences between the two groups of economies and heterogeneity within each country. They only included human capital in the productivity equation. Similarly, Crespi & Zuniga [2012] analyzed six Latin American countries, including Argentina, Chile, Colombia, Costa Rica, Panama, and Uruguay. One key feature of their paper was that the authors adapted the CDM model to specifically analyze developing economies. Interestingly, the authors explicitly state that "The introduction of human capital, which includes researchers and other personnel in R&D, may introduce endogeneity problems due to the overlap with the R&D expenditure variable".

Also, there have been studies that included human capital for individual countries. Janz *et al.* [2004] incorporated human capital in their model as the number of individuals who graduated from a university over total employment. They applied a CDM model to analyze Germany and Sweden and evidenced various similarities between both economies. Their two parameters of interest (the elasticity of labor productivity with respect to innovation output and the elasticity of innovation output with respect to innovation input) were not statistically different between these European nations. Lööf & Heshmati [2006] included two human capital variables: the percentage of engineers and administrators relative to total employment. They analyzed Swedish enterprises and found that the share of engineers is significant for manufacturing, but not for services; however, the other measure that they used for human capital was insignificant in both cases.

Continuing in this same line of research, Mairesse & Robin [2009] used the proportion of employees with higher education in the workforce and included it into their structural approach for analyzing French companies. These researchers estimated two models, one sequential and one simultaneous, and obtained very similar results, thereby suggesting that their findings are fairly robust. Hall *et al.* [2012] included human capital with two measurements: the number of employees with high school and college diplomas and the number of employees that are executives (white-collar) workers and focused on the effect of ICT for Italian companies. In particular, they attempted to find two types of positive externalities: first, between R&D and ICT in innovation and production (but did not find any); and second, between R&D and worker skill in innovation, which was found to be statistically significant.

3 Data

The data used in the present paper are taken from the 2 different sources, the Survey of Development and Technological Innovation or *"Encuesta de Desarrollo e Innovación Tecnológica"* –EDIT– and the Annual Manufacturing Survey or *"Encuesta Anual Manufacturera"* –EAM– both carried out by the National Department of Statistics of Colombia, DANE (by its acronym in Spanish). The EAM aims to obtain information on the manufacturing sector of the economy to improve knowledge of its structure, characteristics, and evolution (see Eslava *et al.* [2004] for the relevance of this survey in the literature of industrial economics). The EDIT mainly focuses on innovation-related topics and covers several dimensions of innovation and follows the methodology of the Oslo Manuals [OECD, 2002, 2005]. The universe of survey comprises firms with 10 or more employees and/or with a value of production in excess nearly of $45,000 USD per year. We use mainly the wave 2009-2010 of the EDIT which has information on the human capital used by the firm. For the lagged of the main variables we used a wave before (2007-2008).

The sample is finally reduced to 6,326 firms due to merging the surveys, the use of lagged indicators, and the availability of variables. Table 1 show the definitions of the variables and table 2 shows the descriptive statistics for main variables of the sample used to perform the econometric estimations. The variables are the traditional set of information used in empirical applications of a CDM-type model in developing countries, except by the information on human capital (see Crespi & Zuniga [2012],Crespi *et al.* [2016] and Gallego *et al.* [2015]. The first two columns show the mean and standard deviation for the total of the sample. We then discriminate for those enterprises that do not report R&D expenditures (R&D decision = 0) and for those who have positive R&D investments (R&D decision = 1), The last column presents a simple mean difference test to check statistically whether or not there are differences between those who spend on R&D and those who do not. As can be noted from the table 2, the only indicator that does not present statistical differences between the two subsamples is the human capital without considering workers in R&D; all other variables are statistically different.

Some interesting figures from the descriptive statistics are the following (see table 2): 77 employees is the average number of workers for a firm in our sample, 169 for those reporting R&D expenditure positive and 66 for the enterprises that reported zero expenditures in R&D, investments on R&D are more common on large firms as the standard literature has shown (see Hall *et al.* [2012]). As literature on innovation for developing economies suggest, patents are very rare: only 0.7% of the total number of firms presented patent protection (see Crespi & Zuniga [2012]. This same indicator is 2.6% for companies that spend in R&D and only around 0.05% among those companies that do not spend in R&D. 29% of the firms reported market sources of information to be important, more than the scientific and public sources with 10.3 and 26%, respectively.

Table 1: Variables Definition

Variables (*Math name*)	Definition
R&D decision (*R&Ddec*)	Dummy equal one if the firm reported positve expenditure in R&D
R&D expenditure (*R&Dexp*)	Logarithm of the R&D expenditure
Innovation (*Inn*)	Dummy equal one if the firm reported any type of innovation
Productivity (*Prod*)	Logarithm of sales per employee
Endogenous human capital (*HK*)	Number of workers in R&D as a proportion of the total number of workers
Exogenous human capital (iv_1)*	Employees with technical or higher studies not working in R&D
Technicians and Professionals in R&D	Tech. and prof. working in R&D as a % of total number of Tech and professionals
Post-graduates in R&D	Post-graduates working in R&D as a percentage of total number of post-graduates
Firm size	Logarithm of the number of employees
Firm age	Logarithm of the number of years since the company was founded
Physical capital	Logarithm of physical capital
Foreign capital	Dummy equal to one if the firm has foreign ownership
Patent protection	Dummy equal one if the firm reported patent protection
Market power	Participation of the firm in the market
Cooperation in R&D	Dummy equal to one if the firm cooperated in R&D with others institutions
Market sources of information	Dummy equal to one if the firm found market sources of information important
Scientific sources of information	Dummy equal to one if the firm found scientific sources of information important
Public sources of information	Dummy equal to one if the firm found public sources of information important
Internal risks	Dummy equal to one if the firm reported internal risks as obstacles for innovation
Financial risks	Dummy equal to one if the firm reported financial risks as obstacles for innovation
External risks	Dummy equal to one if the firm reported external risks as obstacles for innovation

* iv_1 is actually the lagged value of Exogenous human capital

4 Methodology

As previously mentioned, we are going to use a structural CDM model following Crespi *et al.* [2016] as our empirical specification. In a structural model, there is the great advantage that equations represent

Table 2: Descriptive Statistics

Variables (*Math name*)	Total Mean	Total Sd	R&D decision=0 Mean	R&D decision=0 Sd	R&D decision=1 Mean	R&D decision=1 Sd	Mean difference test
R&D expenditure (*R&Dexp*)	0.597	1.855	0	0	5.802	1.788	-244.469***
Innovation (*Inn*)	0.284	0.451	0.283	0.451	0.953	0.209	-33.9188***
Productivity (*Prod*)	10.338	1.046	10.296	1.034	10.695	1.081	-9.2745***
Endogenous human capital (*HK*)	0.041	0.119	0.029	0.1	0.147	0.192	-25.233***
Exogenous human capital (iv_1)*	0.27	0.239	0.269	0.241	0.279	0.22	-1.049
Technicians and Professionals in R&D	0.082	0.201	0.062	0.179	0.259	0.281	-24.935***
Post-graduates in R&D	0.063	0.213	0.042	0.176	0.25	0.363	-24.739***
Firm size	77.514	173.861	66.937	150.968	169.558	292.605	-14.508***
Firm age	24.409	14.015	23.955	13.611	28.363	16.628	-7.641***
Physical capital	10.018	0.0212	9.970	0.022	10.438	0.057	-6.4933***
Foreign capital	0.063	0.243	0.056	0.23	0.121	0.327	-6.4933***
Patent protection	0.007	0.082	0.005	0.068	0.026	0.159	-6.3253***
Market power	0.015	0.054	0.013	0.046	0.037	0.093	-11.255***
Cooperation in R&D	0.184	0.388	0.131	0.338	0.647	0.478	-35.1665***
Market sources of information	0.292	0.455	0.220	0.003	0.826	0.009	-50.373***
Scientific sources of information	0.103	0.304	0.065	0.002	0.403	0.012	-42.146***
Public sources of information	0.259	0.438	0.192	0.003	0.763	0.010	-49.151***
Internal risks	0.303	0.459	0.242	0.428	0.831	0.375	-31.0325***
Financial risks	0.249	0.432	0.192	0.394	0.741	0.439	-30.665***
External risks	0.258	0.437	0.202	0.401	0.744	0.437	-29.988***
Observations	6,326		5,674		652		

* iv_1 is actually the lagged value of Exogenous human capital

causal relationships rather than mere statistical associations Goldberger [1972]. The original CDM approach attempts to tackle two important econometric problems: selectivity and simultaneity. The selection problem might arise because only some enterprises have positive expenditures on R&D, and it is very likely that they are not randomly selected: companies auto-select themselves to do so. Maybe characteristics of firms spending in R&D systematically differ from the characteristics of enterprises that do not, which could be precisely why they made the decision on R&D expenditure in the first place. Consequently, a simple linear regression explaining R&D expenditure for the whole population might be biased. We control for selectivity by applying Heckman's methodology (see Heckman [1979]). However, endogeneity originated by simultaneity is present when including research in the innovation equation and innovation in the productivity equation. The CDM model also addresses this problem when including adjusted values from previous stages.

Human capital is important for increase firm's productivity and as a driver for innovation (see Aghion *et al.* [2005] and Hall *et al.* [2012]), which is why taking this variable into account for a CDM approach makes perfect sense. Empirically, as shown in the literature review, there are many studies incorporating human capital into their models to try to better explain innovation and productivity (Hall *et al.* [2012]; Crowley & McCann [2018]). Even for the Colombian case, Gallego *et al.* [2015] modified the CDM model to include human capital. Our main argument is that the inclusion of human capital into the context of a modified CDM model may lead to additional econometric problems, such as endogeneity. In fact, Crespi & Zuniga [2012] explicitly mention this issue as discussed section 2.2. Some empirical approaches that attempt to incorporate measures of human capital do so using the lagged of the variable rather than current values; this method might alleviate the problem to a certain level.

Nonetheless, we propose to better tackle this issue using the instrumental variable technique, which could be a powerful tool for estimating structural equations using non-experimental data [Wooldridge, 2002]. As far as we know, this is the first work trying to correct the possible endogeneity of human capital in the equation of R&D investment decision (the first stage) using IV methodology in a CDM context. The variable we instrument is the endogenous human capital. In order to instrument this variable, we use two instrumental variables in our main model. The IVs we propose are: (i) the lagged value of exogenous human capital and (ii) the lagged value of endogenous human capital. Our preferred IV variable is the exogenous human capital, which we defined as the proportion of workers with technical or higher studies as a proportion of the total of employees without taking into account those who carry out R&D tasks. This IV affects the decisions of human capital of the firm, but we expect that it is not related with any decision on R&D investment at the current and the previous year. We include the second IV variable and perform four tests for the instruments: under-identification, weak-identification, over-identification and exogeneity.

In subsection 4.2, we present a modified version of the CDM model by Crespi *et al.* [2016] in order to include human capital into the analysis tackling endogeneity issues through the instrumental variable technique at the first stage of the CDM structure. Our model comprises three different stages: (i) R&D equation: firms decide on R&D expenditure by taking human capital into account; (ii) innovation equation: innovation is produced as a result of the investment in the first stage; and (iii) productivity equation: the production function of the firm is modeled including innovation from stage two as an input of production.

4.1 Main variables

In this section we will discuss relevant factors about the variables we use in our model. Our regressors are mainly based on Crespi & Zuniga [2012] [2]. In the first stage of our model, we add human capital

[2]It is important to note that their approach is constrained due to the fact that they only include variables available for all the countries they are analyzing; they must do this because comparability is essential for their research

(endogenous human capital), firms' age, market power, and dummies for obstacles to innovation to what Crespi and Zuñiga had in their paper. We also include dummies for region to control for possible unobserved characteristics of location. In the second stage, we include: predicted R&D investment from the first stage, size, foreign capital and human capital. Finally, in the third stage we include the predicted value of innovation from second stage, physical capital, size and age. In all stages we also include dummies of three-digit industry codes (CIIU, for Spanish acronyms) to control for possible unobserved characteristics of the industry. We now try to explain the most important aspects of the set of variables included in our estimations:

Human capital

As mentioned, we include human capital into the model trying to correct the problems that arise when doing so. Since the endogeneity of this variable will arise mainly due to the overlap between qualified workers and R&D expenditure, we divide human capital into two different indicators: exogenous and endogenous human capital. We define *exogenous human capital* as the proportion of workers with technical or higher studies as a proportion of the total of employees without taking into account those who carry out R&D tasks, which isolates this variable from the overlap problem and makes it much less likely to lead to endogeneity issues. Moreover, we define *endogenous human capital* as the number of workers carrying out R&D tasks as a percentage of the total number of workers. This variable will capture the overlap problem. The idea behind this separation is that it does not only matters for innovation and productivity to have educated workers, but it is also relevant what types of activities those workers perform within the firm.

Age

Age has been proposed as a determinant of the R&D process by several authors. For example, García-Quevedo *et al.* [2014] studied the importance of age as a determinant of the R&D process, finding important differences between young and mature firms, we include this variable as a control variable in our model.

Market power

Market power has received attention for its role in R&D and innovation for quite a long time now. Even Schumpeter discussed the effects of market power in innovation, pointing out two different effects, both of which would boost innovation [Cohen & Levin, 1989]. However, Vossen [1999] argues that this variable plays a more important role in R&D than in innovation itself. In our estimation strategy, we include this variable in both equations of R&D (propensity and intensity).

Information sources and obstacles for innovation

We include six dummy variables to control for information sources and obstacles to innovation. The first three —market, scientific and public sources of information— differ from Crespi and Zuñiga because we use dummies, whereas they include them as an index between 0 and 100. The other three —internal, financial and external risks— relate to different types of obstacles to innovation, which by definition, influence innovation and might also impact on productivity.

4.2 Our modified specification

In our specification of the CDM structure, the first stage presents an additional econometric problem: the inclusion of human capital leads to endogeneity. As explained, we aim to address this problem using the IV method. Instead of calculating the R&D stage in two steps, as most other studies have done, we perform three steps. Since we need to calculate the probability of spending in R&D —and human capital is an important determinant of this probability—, we run an instrumental variable probit in two stages and then calculate the Inverse of Mill's Ratio[3] , to include it into (3), the equation where the logarithm of the expenditure of R&D is regressed against a set of regressors x. Formally, with the modified version of the CDM we have three equations for the first stage (equations 1 to 3) instead to the traditional two equations considered in the first stage of a standard CDM model (see Hall *et al.* [2010]:

$$HK_i = iv_1\gamma_1 + iv_2\gamma_2 + z_i'\rho + \omega_i \tag{1}$$

where HK_i represents what we call endogenous human capital and iv_1 and iv_2 are the instrumental variables we use. z_i is a vector of determinants of the R&D decision used also in 1. As previously mentioned, these are the lagged value of exogenous human capital, and the lagged value of endogenous human capital respectively. It is important that $\gamma_j \neq 0,\ \ j = 1, 2$. The vector of variables z_i includes the same set of variables used on the investment decision, as follows: size of the firm, age, external capital measure, patent measure, part of a multinational group, exporting behavior, public subsidies for R&D,

[3]The Inverse of Mill's Ratio is defined as $\frac{\phi(Z_i)}{1-\Phi(Z_i)}$ where $\phi(Z_i)$ and $\Phi(Z_i)$ are the density and the distribution function for a standard normal variable. See Heckman [1979]

cooperation on innovation, several sources of information to implement R&D and barriers to innovate, those variables defined in table 1. Equation (2) estimates the impact of various factors in the R&D decision, mathematically,

$$R\&Ddec_i = z_i'\rho + \hat{HK}_i\phi + \zeta_i \tag{2}$$

where z_i is a vector of determinants of the R&D decision, as defined above, and $\hat{HK}_i$ is the instrumented version of HK_i obtained from equation (1). Equation (2) is estimated using a probit model. Afterwards, we estimate the Inverse of Mill's Ratio to include it into (3) —the R&D expenditure equation— to control for selectivity following Heckman's procedure

$$R\&Dexp_i = x_i'\beta + \hat{HK}_i\nu + IMR_i\theta + \varepsilon_i \tag{3}$$

where $R\&Dexp_i$ represents the R&D expenditure of firm i, x_i is a subset of the vector z_i by excluding the size and IMR_i is the Inverse Mills Ratio mentioned above. Equation (3) is estimated as a linear regression model.

The next 2 stages of the model are treated as a standard CDM model, they are formally represented in (4), which is the innovation equation that we estimated as a probit model:

$$Inn_i = v_i'\delta + R\&\hat{D}exp_i\varphi + \hat{HK}_i\eta + \varepsilon_i \tag{4}$$

where $R\&\hat{D}exp_i$ is the predicted value of $R\&Dexp_i$ calculated from (3) and v_i is a vector of variables that are important for innovation, similar to Crespi & Zuniga [2012]. The equation (5) refers to the productivity equation and it is estimated as a linear regression model, formally:

$$Prod_i = k_i'\pi + I\hat{n}n_i\vartheta + \mu_i \tag{5}$$

where $Prod_i$ is the logarithm of productivity of firm i, k_i is a vector of variables that are relevant for productivity and $\hat{Inn_i}$ is the the predicted value of Inn_i estimated from equation (4).[4]

5 Results

We divide this section into three subsections. In subsection 5.1 we present our most important results; two models using all the data available we compare them. In subsection 5.2 we estimate two models using the IV methodology for both but restricting the data for each model depending on the size of the firms involved. Finally in subsection 5.3 we estimate 2 models and restrict the data for type of level of human capital.

5.1 Basic results

In this section, we show our main results. Table 3 shows the outcome for two CDM models, the first one —the "naive" version— is basically how the model would be calculated without the IV correction we propose. In the second one —the "instrumented" version— we instrument endogenous human capital with both the lagged exogenous human capital and the lagged endogenous human capital. The results for both versions of the model are quite similar, however there are some key differences, which we like to point out. One thing that distinguishes both specifications is the difference of the effect of human capital. In the first stage, endogenous human capital in the naive version matters for both R&D intensity and propensity; In the instrumented version, endogenous human capital matters only for the propensity equation of R&D, but the coefficient is higher than the one calculated in the naive version. Another important difference between the naive and the instrumented versions are the effect of the estimated R&D on innovation, being almost 70% higher the one calculated in the instrumented version compared to the naive estimation. Finally, it is worth noting that the effect of estimated innovation on productivity is fairly similar at around 0.26 with 1% statistical significance. In this sense, we can said that human capital play an important role on the decision to invest on R&D and on the innovation behavior, something that can help policy makers to design policies that help firms to include educated workforce in the innovation process independent of the amount of private investments on R&D and to push firms into the innovative process.

An essential part of our work has to do with the inclusion of human capital using the IV methodology to control de endogeneity that may arise. In table 4 we present results of four test for our instruments.

[4] All the equations, from 1 to 5 were estimated using bootstrap.

Table 3: Naive vs Intrumented

	First Stage				Second Stage		ThirdStage	
	(1)	(2)	(3)	(4)	(5)		(6)	
Independent variables	Naive	Naive	Instrum	Instrum	Naive	Instrum	Naive	Instrum
Endogenous human capital	1.320***	1.450***	5.411***	0.0177	2.397***	2.050***		
	(0.172)	(0.530)	(1.391)	(0.810)	(0.277)	(0.283)		
Firm size	0.169***		0.212***		0.113***	0.096***	0.126***	0.127***
	(0.027)		(0.031)		(0.005)	(0.004)	(0.0133)	(0.0119)
Firm age	0.010	-0.172	0.047	-0.239**			-0.0849***	-0.0816***
	(0.047)	(0.122)	(0.050)	(0.121)			(0.0222)	(0.0215)
Foreign capital	-0.163	0.0666	-0.143	0.0895	-0.042**	-0.038*		
	(0.105)	(0.242)	(0.107)	(0.245)	(0.020)	(0.019)		
R&D expenditure (predicted)					0.079***	0.133***		
					(0.011)	(0.013)		
Innovation (predicted)							0.263***	0.254***
							(0.0539)	(0.0507)
Physical capital							0.127***	0.127***
							(0.0109)	(0.0123)
Constant	-3.332***	4.836**	-3.550***	6.498***			8.584***	8.574***
	(0.278)	(1.913)	(0.294)	(1.264)			(0.169)	(0.148)
Observations	6,326	652	6,326	652	6,326	6,326	6,326	6,326

Dependent variables: (1) and (3): R&D decision. (2) and (4): R&D expenditure. (5): Innovation. (6): Productivity
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the first place, we perform an under-identification test in which we reject the null hypothesis that the equation is under-identified, however we want to verify that the model is not weakly identified. With this in mind, we perform a weak-identification test in which we obtain an F statistic of approximately 90 which is above the estimated 10% threshold of 19.9 meaning our instruments aren't weak. Now, since we have more than one instrument for this model, we can run an over-identification test; and with a Sargan-Hansen statistic of 0.012 we do not reject the joint null hypothesis that the instruments are valid. Finally we run a Wald test the exogeneity and reject the null hypothesis of no endogeneity, which means that, endogeneity is in fact an issue and the proposed IV correction is pertinent. We would also like to mention that in the estimation of equation (1) both instruments were positive and statistically significant at 1%; our estimations showed that $\gamma_1 = 0.021$ and $\gamma_2 = 0.134$.

Table 4: Instruments tests

	Under-identification†	Weak-identification‡	Over-identification††	Exogeneity ‡‡
Statistic	178.185	90.399	0.012	9.25

† Anderson canon. corr. LM statistic.
‡ Cragg-Donald Wald F statistic
†† Sargan-Hansen statistic
‡‡ Wald test of exogeneity

5.2 Size

Table 5: Small Vs. large firms

	First Stage				Second Stage		Third Stage	
	(1)	(2)	(3)	(4)	(5)		(6)	
Independent variables	Small	Small	Large	Large	Small	Large	Small	Large
Endogenous human capital	6.169***	0.861	3.221	0.229	2.033***	3.156**		
	(1.555)	(0.845)	(3.394)	(3.134)	(0.276)	(1.481)		
Firm size	0.233***		0.075		0.112***	0.084**	0.115***	0.0170
	(0.039)		(0.134)		(0.006)	(0.037)	(0.0159)	(0.0628)
Firm age	0.036	-0.297**	0.195	-0.296			-0.101***	0.0530
	(0.055)	(0.131)	(0.147)	(0.435)			(0.0200)	(0.0630)
Foreign capital	-0.168	0.451	-0.338*	-0.0699	-0.095***	0.019		
	(0.146)	(0.332)	(0.197)	(0.568)	(0.024)	(0.045)		
R&D expenditure (pred)					0.131***	0.044***		
					(0.013)	(0.015)		
Innovation (pred)							0.203***	0.715**
							(0.0488)	(0.343)
Physical capital							0.118***	0.167**
							(0.0109)	(0.0674)
Constant	-3.803***	6.150***	-3.377***	7.056			8.747***	8.324***
	(0.385)	(1.271)	(0.982)	(4.658)			(0.166)	(0.706)
Observations	5,717	503	482	149	5,758	499	5,758	499

Dependent variables: (1) and (3): R&D decision. (2) and (4): R&D expenditure. (5): Innovation.(6): Productivity
Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In this subsection, we estimate two models with the same structure compared to the Instrumented-model presented in 5.1. The firs one, only for small firms –firms with 200 or less workers–, and the second for large firms –firms with more than 200 workers–. Results of this estimation are presented in Table 5. One thing worth highlighting is that endogenous human capital is important for explaining R&D propensity only for small firms. Endogenous human capital does not show any significant effect on R&D intensity, nor small or large firms. Another interesting fact is the coefficient of the predicted value of the R&D expenditure in second stage; it turned out that it has a statistically significant effect for both small and large firms, but the effect for the small firms is noticeably stronger (0.131 vs. 0.044). The coefficient of Firm Size in third equation suggests that size is still important even after isolating small firms, however, size losses relevance for productivity once the firm is large. The impact of the predicted value of innovation on productivity is much stronger for large firms. The most interesting result on table 5 is that human capital is an important driver for investment on R&D and innovation behavior for small and medium firms, compared with big firms in which human capital does not play a substantial role.

5.3 Level of education

Table 6: Technicians & Professionals Vs. Post-graduates

	First Stage				Second Stage		Third Stage	
	(1)	(2)	(3)	(4)	(5)		(6)	
Independent variables	Tec&Pro	Tec&Pro	Post	Post	Tec&Pro	Post	Tec&Pro	Post
Technicians and Professionals in R&D	2.997***	-0.441			1.184***			
	(0.826)	(0.638)			(0.084)			
Post-graduates in R&D			6.519***	-1.083**		0.585***		
			(1.898)	(0.508)		(0.043)		
Firm size	0.212***		0.091***		0.087***	0.093***	0.144***	0.124***
	(0.031)		(0.032)		(0.004)	(0.004)	(0.0138)	(0.0110)
Firm age	0.029	-0.225*	0.003	-0.236*			-0.0870***	-0.0794***
	(0.049)	(0.123)	(0.053)	(0.121)			(0.0219)	(0.0246)
Foreign capital	-0.079	0.0438	-0.049	-0.0105	-0.015	-0.036*		
	(0.108)	(0.249)	(0.128)	(0.243)	(0.017)	(0.021)		
R&D expenditure (pred)					0.130***	0.211***		
					(0.010)	(0.010)		
Innovation (pred)							0.116***	0.264***
							(0.0367)	(0.0534)
Physical capital							0.127***	0.127***
							(0.0117)	(0.00979)
Constant	-3.577***	5.976***	-3.220***	6.294***			8.569***	8.573***
	(0.295)	(1.345)	(0.309)	(1.045)			(0.140)	(0.141)
Observations	6,326	652	6,326	652	6,302	6,302	6,302	6,302

Dependent variables: (1) and (3): R&D decision. (2) and (4): R&D expenditure. (5): Innovation.(6): Productivity
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In table 6 we present the results for two intrumented-models that have different measures of human capital. The first one, which we call Tech&Pro, uses the technicians and professionals working in R&D as a percentage of total number of Technicians within the company as a measure of human capital, whereas the second is the same indicator but for post-graduates, which we call Post. The idea here is to see if any difference in the impact of innovation on productivity can be explained by the level of education of workers.

In the first stage, for both cases –Tech&Pro and Post– the human capital indicator matters for the propensity equation, and surprisingly we obtain a negative effect of post-graduates in R&D in the intensity equation. One possible explanation for this might be the lack of organizational structure; we have found that the correlation between post-graduates in R&D and R&D expenditure is negative for those enterprises with a defined R&D division, which is quite strange. It might be possible that even though firms have a formal R& division, they still perform R&D activities –and have post-graduates workers– outside the R&D division.

The impact of the estimated R&D expenditure on innovation and the effect of predicted innovation on productivity are stronger for post graduates compared to Technicians and Professionals in R&D, although in all cases coefficients are positive and statistically significant at 1%. In almost all cases, table 5.3 show a consistent higher effect from employees with higher levels of education, which is a pretty intuitive result. The most important policy implication of this type of human capital is the promotion for high level educated workers on the production process at the firm. Even if technicians are an important part of the innovation process, the most significant effects of human capital on innovation investments and innovation outcomes occurs when a firm increases the proportion of post graduate workers (those with a Master or PhD diploma).

6 Conclusions

In this paper, we have studied the relationship between human capital, R&D investment, innovation, and productivity. We did so by estimating three different versions of the CDM model following Crespi & Zuniga [2012] and Crespi *et al.* [2016] and their approach for developing economies. We have included human capital into the analysis and tried to control the endogeneity that the addition of this variable adds to the model. Through the IV methodology, we tried to correct the endogeneity of a measure of human capital. We have performed our econometric analysis based on Colombian data at the firm level for the period 2009–2010 and found several interesting results. We use two instrumental variables and perform four different tests for those instruments (Under-identification, weak-identification, over-identification and exogeneity). In all four cases we obtained the empirically desired result. Using the Wald test of exogeneity, for instance, helped us concluding that including our measure of human capital within the analysis not correcting the endogeneity would have led to biased results; therefore, our methodology is pertinent in this regard.

Throughout our calculations several important results hold no matter the specificity. In all the models presented here, the effect of R&D expenditure on innovation in second stages and the impact of innovation on productivity in third stages, are always positive and statistically significant at 1%. This speaks of the robustness of our model. Another common factor across all our estimations is that no matter the way of quantifying human capital, according to our econometrics results, it plays an essential role in the relationship between innovation and productivity in Colombian manufacturing firms; this findings may seem very intuitive and trivial, but highlights the importance of considering it in the analysis in a CDM context.

There are several lessons for policy implication after consider the causal effect of human capital on the investment on R&D decisions at the firm level. In general, human capital plays an important role on the decision to invest on innovation activities, but not necessarily on the amount of the investment. This result is important for policy makers because it helps to generate important human capital policies regardless of the amount of investment by firm. The second lesson is the differentiated effect for size of the firm. Small and medium firms that decided to invest on innovation activities are more positive affected by the inclusion on human capital on the knowledge creation process compared with the similar large firms. Finally, the type of human capital matters, the human capital plays and important role on the knowledge creation process if the human capital is the most educated one, thus means if the proportion of Master or PhD workers increases.

Nevertheless, there are still some issues regarding the relationship between human capital, innovation, and productivity that need to be understood. Further research is challenging and greatly desirable. One of the recommendations for further research is the inclusion of time within the analysis. For this paper, we employed a cross section of firms, which allowed us to capture short-run relationships between variables. Adopting a panel data approach would enrich the analysis because it would allow to study longer term relationships thereby capturing more of the dynamism and complexity of innovation. Some of its effects are impossible to capture with a cross sectional data analysis. Another stimulating focus for future research is the measure of innovation. In this empirical exercise, we used innovation as an aggregated indicator; however, it would be very interesting to discriminate different types of innovation. Probably higher educated workers who are not engaged in R&D tasks within a firm are better enhancers of non-technological innovation; moreover, educated people dedicated to R&D activities may play a more important role in technological innovation. Further research with more specific measures of this technological and non–technological innovation and its relationship with human capital are relevant. A third recommendation for further research should consider the importance of different approximations to the problem; the phenomena studied in this paper —especially human capital and innovation— have strong social components, which make them far too complex to be fully analyzed and understood from a single disciplinary viewpoint. Multidisciplinary perspectives could lead to a more profound knowledge of each of these concepts and, consequently, a broader understanding of the relationship among them. Such approaches are highly encouraged.

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