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Roberto Álvarez, Matteo Grazzic, Diana Suárez, Sebastian Vergara

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ARTÍCULOS

Departamento de Economía

Innovation and Entrepreneurship in Latin America: Recent Evidence and Challenges

Innovación y Emprendimiento de América Latina: Evidencia Reciente y Desafíos

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Abstract

In this paper, we discuss several aspects related to innovation and entrepreneurship in Latin America (LATAM). First, we document how LATAM lags behing high-income economies using various innovation indicators and how heterogeneity is a relevant issue for the region. Then, we review the main research topics related to innovation and entrepreneurship covered by economic academic research focused on the region. Within this context, we summarize the main results and contribution of the selected papers for this special issue.

Key words: *Innovation, entrepreneurship, research, Latin America.*

JEL Classification: *L26, M13, O31.*

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Resumen

En este documento, se discuten varios aspectos relacionados con la innovación y el emprendimiento en América Latina (AL). En primer lugar, se documenta cómo AL está rezagada respecto a las economias de altos ingresos usando varios indicadores de innovación y cómo la heterogenidad es un tema relevante para la región. Luego, se revisan los principales temas de investigación en las areas de innovación y emprendimiento abordados por la investigación economica centrada en la región. Dentro de este contexto, se resumen los principales resultados y la contribución de los trabajos seleccionados para este numero especial.

Palabras clave: *Innovación, emprendimiento, investigación, América Latina.*

Clasificación JEL: *L26, M13, O31*

1. Introduction

Assessing innovation performance, whether at the firm, sector, country, or global level, is a complex challenge. This requires considering a broad range of aspects, including economic, social, technological, and institutional dimensions. Thus, it is crucial to examine a comprehensive array of indicators that capture different innovation facets to fully understand innovation capabilities.[1]

As a general context, it is interesting to notice that even before the pandemic there were indications that the technological efforts were diverging across countries by level of development. Between 2015 and 2020, the change in R&D investments was positively correlated with GDP per capita (Figure 1). Thus, more advanced economies tended to increase R&D investments more intensively than less developed economies. The decline of trade as a growth engine observed in the last decade, coupled with the ongoing fragmentation of the global economy and its effects on foreign direct investment, raises significant concerns about the future of technological asymmetries across economies, even within developing economies.

There are relevant challenges for Latin American countries to catch-up the productivity and technology of the developed world. This requires private ef-

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1 As such, innovation indexes summarize and combine various innovation aspects, for example human capital, research, infrastructure, technology outputs and institutional capacities, among others. This approach, however, lacks theoretical foundations and could suffer from biases, depending on the relative importance of each aspect into the overall index.

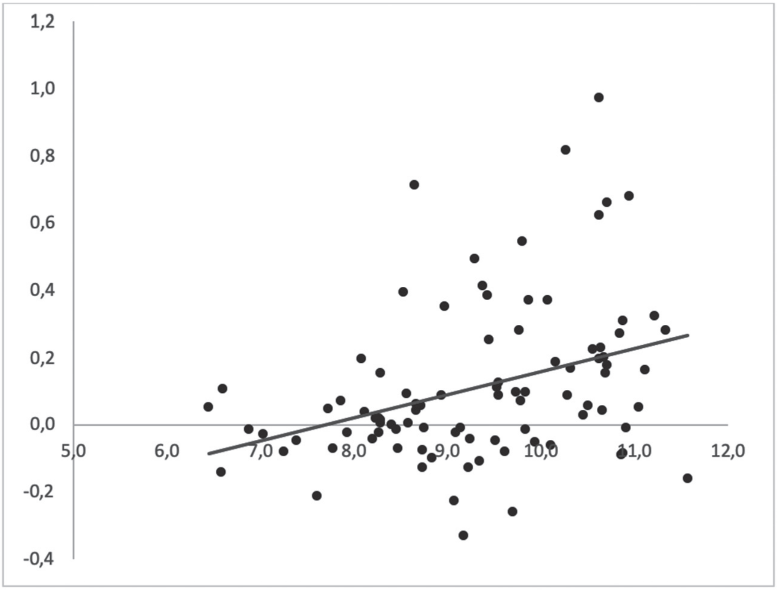
forts and public incentives. The academic research on these issues should be relevant for implementing the right initiatives. This has been the main objective of the Latin American Network on Economics of Innovation and Entrepreneurship since the first conference held in Washington D.C. in July 2017. The papers in this special issue were presented at the last conferences held in Santiago, Chile in 2022 and in Guayaquil, Ecuador in 2023.

This paper is structured as follows. The second section reviews the Latin American comparative performance using several innovation indicators. The third section discusses about firm's heterogeneity. Section fourth presents some facts about recent empirical evidence. The fifth section summarizes the papers in this issue.

2. Latam Innovation Performance

A traditional starting point is R&D investments, which mirror the technological efforts to generate, absorb, and utilize knowledge. As such, R&D investments are crucial inputs for introducing product and process innovations (Lööf, et al., 2017). In recent decades, R&D investments in Latin America showed a modest increase (see Table 1). Between 2000 and 2015, R&D investments as a share of GDP climbed from 0.51% to 0.72%. However, it then declined to 0.59% by 2020, following the end of the commodity boom in 2014/15. By contrast, developed economies and East Asian economies show a more substantial expansion of R&D investments. R&D investments as a share of GDP in developed economies increased from 2.23% in 2000 to 2.99% in 2020. Thus, the R&D gap between Latin America and developed economies expanded from 1.72 to 2.40 percentage points. In East Asia, R&D investments as a share of GDP expanded from 0.67% in 2000 to above 2.0% of GDP in 2020.

FIGURE 1
CHANGE IN R&D INVESTMENTS OVER GDP BETWEEN 2020 AND 2015 AND GDP PER CAPITA 2015
PERCENTAGE POINTS AND NATURAL LOG



Source: Authors' elaboration based on data from UNESCO and IMF.

Since 2020, the R&D gap between Latin America and developed economies has likely expanded further. For developed economies, the pandemic crisis and the war in Ukraine uncovered critical supply chain weaknesses and productive vulnerabilities, underscoring domestic resilience and national security issues over efficiency considerations. Also, the growing geopolitical rivalries, together with the green energy transition, are prompting United States, China, and the European Union to expand their policies to retain or enhance competitive advantage (OECD, 2023). Therefore, developed economies are increasingly supporting R&D investments, particularly in high-tech sectors, as well as supporting low-carbon innovations. In contrast, innovation policy efforts in developing economies remain much smaller in scale and scope, and public budgets towards science, innovation and technology are only gradually recovering from substantial cuts in the pandemic crisis.

TABLE 1
INNOVATION INDICATORS, 2000-2020
WEIGHTED AVERAGES

Region	Indicator	2000	2005	2010	2015	2020
Developed economies	R&D	2.23	2.24	2.38	2.56	2.99
	Researchers	3,260.60	3,549.34	3,807.15	4,166.83	4,448.50
	Patents	797.16	829.57	813.62	856.21	799.84
	Publications	973.52	1,175.54	1,277.50	1,341.03	1,403.17
Latin America	R&D	0.51	0.53	0.65	0.72	0.59
	Researchers	253.17	382.12	496.79	569.56	586.2
	Patents	11.95	13.84	12.74	13.63	14.93
	Publications	61.94	89.68	140.55	166.96	226.02
East Asia	R&D	0.67	1.00	1.37	1.70	2.03
	Researchers	562.91	845.53	946.45	1,208.43	1,563.88
	Patents	17.71	54.97	168.16	545.72	760.75
	Publications	67.67	141.65	227.45	283.41	434.67

Source: Authors' elaboration based on data from UNESCO and WIPO.
Note: R&D corresponds to R&D as a share of GDP; researchers are the number of full-time equivalent researchers per million inhabitants; patents are patents applications per million inhabitants; publications are the number of scientific publications per million inhabitants. For Brazil, the data for researchers in 2020 is not available. For the regional calculation, we used the same number of researchers that Brazil reported in 2015.

Another indicator of innovation refers to the number of scientific researchers, which is also a key input for innovation. In the last two decades, the number of full time-researchers per million inhabitants in Latin America has more than doubled. As such, the region was able to reduce the gap with respect to developed economies, which have already accumulated a critical mass of researchers. East Asian countries have nearly tripled their scientific research base, showcasing an even more impressive expansion.

Regarding patents applications –usually considered as an outcome of innovation efforts–, Latin American economies have not been able to catch-up with the performance of developed economies (Table 1). The average number of patents applications per million inhabitants has only increased marginally. This poor performance is explained mainly by the low levels of R&D investments and skills of the labour force, weak legal and regulatory frameworks and lack of technological infrastructure. By contrast, the performance of East Asia in the last two decades was remarkable, driven by China. Meanwhile, the scientific publications exhibit a relatively strong expansion in Latin America. The number of scientific publications per million inhabitants in the region increased nearly fourfold in the past two decades.

This confirms that Latin America performed poorly regarding innovation indicators and did not substantially close innovation gaps in the recent decades.[2] There is no single factor to explain the poor innovation performance in the region, and crucial aspects are a largely limited scientific community and low levels of labour force skills, usually including mismatches between educational outcomes and industry requirements (Navarro et al., 2016). In addition, the productive structure is biased towards low-tech sector, which leads a poor innovative dynamic with also low levels of technological spillovers. Manufacturing innovation is highly informal. Thus, R&D investments are low and with a relatively low participation of the private sector.

Also, there is a lack of interactions and cooperation between private sector and universities, and innovative firms tend to operate isolated, without creating downward and upstream linkages. Finally, countries have decided not to embark in transformative innovation policies, amid major structural constrains, including fragile institutional frameworks and lack of financing resources (Peres and Primi, 2019; ECLAC, 2022). In addition, in recent years many countries in the region are facing increasing fiscal constrains to implement innovation policies due to elevated levels of debt, rising debt servicing costs and large output losses from the pandemic crisis (United Nations, 2023).

3. Firms' Heterogeneity, Productivity and Innovation

Most of the economic literature on innovation and productivity assumes firms as homogeneous. However, worldwide empirical evidence indicates that there is significant heterogeneity not only across countries and sectors, but also among firms operating in the same markets (see Table 2). In the United States, Syverson (2004 and 2011) found that -within the same four-digit Standard Industrial Classification (SIC) code in the manufacturing sector- the plant in the 90th percentile of the productivity distribution has almost twice as much output than the plant in the 10th percentile with the same measured inputs. Even when homogenous products industries are considered - such as solid fiber boxes or ready-mixed concrete - large differences persist (Foster et al., 2008). The existence of high productivity dispersion has been confirmed by several other country-specific studies (see, for example Disney et al., 2003 for results on the United Kingdon, Ito and Lechevalier 2009 for Japan and Crespi and Zuñiga, 2012, Fiorentin et al. 2021, and Molina-Domene y Pietrobelli, 2012 for Latin America).

[2] This analysis uses weighted averages (according to GDP) for calculating regional indicators. However, using simple averages and the median across countries for regional indicators does not alter the main messages.

In developing regions, where economic dualism is a common phenomenon, firms' heterogeneity is usually even more pronounced. For example, in China and India, the average 90–10 TFP ratios was found around 5:1 (Hsieh and Klenow 2009). LAC is no exception. Overall, the region is characterized by large disparities in productivity (Busso et al., 2013; Pagés, 2010), where many low-productivity firms coexist with few firms with high productivity. Using data from the World Bank Enterprise Survey, Grazzi and Pietrobelli (2016) found that the variance between the 90th and 10th percentiles of the labor productivity distribution in the LAC manufacturing sector was approximately 10:1, with most firms clustered at very low levels of productivity, although some highly productive firms also appear in the scenario.

TABLE 2

EMPIRICAL EVIDENCE ON FIRM PRODUCTIVITY DISPERSION

Country	**90-10 percentile average difference in logged TFP**	**90-10 percentile TFP ratio**	**Author**
Japan	0.25	1.28*	Ito and Lechevalier (2009)
United States	0.65	1.91	Syverson (2004, 2011)
United Kingdom	0.91	2.47*	Disney et al. (2003)
Chile	1.31	3.70	Figal Garone et al. (2020)
China	1.59	4.90*	Hsieh and Klenow (2009)
India	1.60	4.95*	Hsieh and Klenow (2009)
Latin America and the Caribbean	1.91	6.72	Figal Garone et al. (2020)

Note: In the cases marked with *, the value was not included in the original papers, but it has been calculated on the basis of the original data in Figal Garone et al. (2020).

Source: Authors´ elaboration.

In a more recent research effort, Figal Garone et al. (2020) confirmed the persistence of high firm productivity dispersion in the region by finding an average TFP ratio between an industry's 90th and 10th percentile firm of 6.72.

It means that the firm at the 90th percentile of the productivity distribution is found to generate almost seven times more output with the same inputs than the 10th percentile firm operating in the same industry. The authors also replicated this analysis in Chile, finding a 90-10 TFP ratio of 3.70. Interestingly, they found similar figures using different levels of industry disaggregation (two-digit industries vs. four-digit industries), concluding that their results do not depend on data structure.

From a theoretical point of view, this situation has been explained in various forms by scholars from different schools of thought. On the one hand, the neoclassical approach stresses the role of market imperfections and particularly of lack of competition, which prevents the correct functioning of the entry-exit mechanism. Without competitive pressures, incumbent firms may face fewer incentives to innovate or improve their products and services. Therefore, poorly performing firms may persist in the market without facing pressure to exit. At the same time, incumbent firms may engage in practices that deter potential entrants. This could include predatory pricing strategies that make it difficult for new firms to establish themselves or compete effectively. This can result in the inefficient allocation of resources, as they continue to be allocated to firms that are not productive or competitive.

On the other hand, evolutionary and managerial approaches refer to the intrinsic characteristics of firms: their internal organization, routines and practices, specific strategies to accumulate technological capabilities, learning, and innovation (See e.g. Dosi, 1988; Lundvall, 1992; Nelson, 1991). In other words, firm performance depends on the unique characteristics embedded within firm-specific decision making, organization, and processes.

Heterogeneity in productivity highlights the fact that not all the firms innovate in the same way or to the same extent, and that their returns to innovation effort largely vary, depending not only on the sector where they operate but also on their characteristics, capabilities, technological orientation, and market positioning.

Related empirical evidence in the region seems to confirm this hypothesis. Morris (2018) found that explicitly accounting for unobserved firm heterogeneity significantly reduces the size of both the effect of innovation input on innovation output and of innovation output on productivity. Specifically, investment in R&D consistently increases the innovation performance of firms operating in the manufacturing sector but its effect is unstable and substantially for firms in the services sector. Crespi et al. (2015), by employing a quantile regression approach, estimated the impact of innovation on productivity in LAC firms, finding that it is remarkably different across productivity quartiles. In other words, innovation has much larger effects on the firms that are already more productive than others. At the upper end of the distribution (the top 10 percent in terms of productivity), the increase in productivity due to innovation is much higher than in the lower quartiles (an increase of no less than 65 percent versus 29-34 percent in the first three quartiles).

These findings have direct implications for both innovation economics research and innovation policy design and effectiveness. One-size-fits-all policies may not adequately address the diverse needs and challenges faced by different types of firms. Detailed research and impact evaluations should throw further light on what kind of specific tools should be employed in each case.

4. Recent Empirical Evidence

To shed light on the main research topics related to innovation and entrepreneurship in Latin America, we look for articles in the top field journals in this area. We use the Scholar Google classification for the top ten journals. These are the following ones: Research Policy, Small Business Economics, Journal of Business Venturing, Entrepreneurship Theory and Practice, Journal of Small Business Management, International Journal of Entrepreneurial Behavior & Research, International Entrepreneurship and Management Journal, Journal of Open Innovation: Technology, Market, and Complexity, Technovation and The Journal of Technology Transfer. We select articles in top journals for looking at high quality research, even we acknowledge that this can be arguable. In total, we find 23 articles published between 2018 and 2024. We start in 2018 because this was the publication year of the previous literature review carried out for the last special issue of the Network of Innovation and Entrepreneurship Economics (RIE). The articles were selected under the following criteria: (i) the question addressed should be related to innovation and entrepreneurship and (ii) the focus is on some Latin American country or whether the region as a whole is part of the research.[3]

Several patterns emerge from this selection. First, most of the articles (about 70%) have been published in Research Policy, the top one field journal according to the Scholar Google classification. This is evidence that research in these topics can be qualified as high quality. Second, most of the articles have focused on issues related to innovation. Few articles analyze aspects of entrepreneurship in Latin America. Third, according to the main question in the article, the emphasis of the research is about the determinants (drivers or obstacles) of innovation. We find that 15 over 23 papers, about 65%, corresponds to this issue. The rest of the articles analyze the impact of innovation on different aspects of performance (22%) and there are three articles summarizing literature on innovation and entrepreneurship in Latin America. Finally,

[3] The list of selected papers is available upon request.

regarding the location of the authors, we look at whether some of the authors of the articles work for some Latin American institution. We find that most of the papers (78%) have at least one author located in the region.

5. This Issue

The paper titled "Inventions, Public Subsidies, and Market Launch: Opportunities and Limits of Patenting Support in Argentina" by Dario Milesi, Carlos Aggio, and Vladimiro Verre delves into an analysis of the Argentinean program "ANR Patentes," which offers grants for patent applications to innovative firms, entrepreneurs, and researchers. The novelty of this paper lays on its original methodological approach in evaluating the results and impacts of a small-scale program, with a particular focus on the post-patenting phase. The authors raise the question of whether patents met market expectations, ultimately concluding that the program successfully stimulated patenting among Argentinean firms and inventors—a significant feat given the low levels of patenting in Argentina. However, the authors assert that merely promoting patent applications falls short of ensuring that innovative products reach the market. They argue that additional, well-coordinated policies are necessary to bridge this gap effectively.

The paper titled "The Impact of Intangible Capital on Productivity and Wages: Firm-level Evidence from Peru," authored by Rafael Castillo and Gustavo Crespi, investigates the influence of intangible assets on firms' productivity and wages in Peru. Utilizing longitudinal firm-level data, the study offers robust estimations of causal relationships. Additionally, the authors reflect about the roles of intangible and tangible assets within the context of a middle-income country, exploring how wages and total factor productivity compete for appropriability of quasi-rents. Through their analysis of capital investments in both types of assets, the authors found that increases in the proportion of intangible assets correlate with elevated levels of total factor productivity, surpassing the returns on investments in tangible assets. Furthermore, they observe that while higher productivity levels are associated with increased wages, this relationship is not fully translated due to imperfect competition in labor markets. This highlights the potential for policy interventions aimed at improving income distribution.

The paper titled "Diverse Knowledge for Diverse Innovation: Evidence from Chilean Firms," authored by Rodolfo Lauterbach, examines the relationship between institutions from the national system of innovation as sources of external knowledge and the innovation performance of Chilean firms, using firm-level data. The research question focuses on identifying the differential impacts of various sources of external knowledge on the specificities of firms' innovation outcomes. In pursuit of answers, the author delves into the Chilean innovation survey, which follows the traditional Oslo Manual framework, to investigate whether the source of knowledge—whether from commercial chains (clients and suppliers), S&T institutions, or government agencies—affects firms' innovation outcomes. The findings reveal that while knowledge gathered from clients influences all types of innovations, knowledge from governmental agencies is positively associated with social innovations, and to a lesser extent, with product and process innovations. None specific association is found for the case of knowledge from competitors. These results offer valuable insights for policy design and firm-level decision-making, suggesting which types of linkages should be fostered depending on the desired innovation outcome.

In the paper titled "Quality Management and Labor Productivity of Formal Companies in Peru: A Non-Experimental Design and Causal Machine Learning Techniques," Mario Tello and Daniel Tello-Trillo examine the effects of quality management tools on the labor productivity of Peruvian firms using firm-level data. Apart from employing non-experimental methodologies and cutting-edge techniques, such as machine learning, the novelty of this paper lies in its assessment of causal relationships between quality management and labor productivity. The authors establish that quality assurance techniques have a positive impact on productivity, particularly among large and medium-sized firms in the manufacturing sector. These findings are consistent across various estimations, affirming not only the positive association between the variables under study but also the methodological contribution of the paper for future applications of the proposed modeling technique.

The paper "Beyond Formal R&D: Firms' Capabilities and Its Innovation Profile. The Case of Argentinean Manufacturing Firms (2014-2016)," authored by Florencia Barletta, Diana Suarez, Gabriel Yoguel, and Florencia Fiorentin, explores the relationship between different innovative strategies and firms' innovation outcomes. Departing from the low levels of R&D investments among Argentinean firms, they investigate different innovative profiles based on different forms of R&D investments (formal and informal, and other innovation efforts). They found that the more significant the role of R&D, the higher the likelihood of achieving product and process innovations. Additionally, the more complex the R&D strategy, the higher the probability of patenting. However, they observed that R&D-based strategies require higher levels and types of capabilities - productive, organizational, connectivity, and absorptive. The novelty of their contribution lays on the methodological approach that considers the presence of micro-heterogeneity, not only in terms of productivity levels but also derived from discretionary choices of firms. Their results contribute to public policy design by shedding light on the relationship between innovation investments and capabilities, and the necessity of articulating different types of innovation public policies.

References

Busso M., Madrigal, L. and Pagés, C. (2013). "Productivity and Resource Misallocation in Latin America", *The B.E. Journal of Macroeconomics*, Vol. 13(1), 903- 932.

Crépon, B., Duget, E. and J. Mairesse (1998). "Research and Development, Innovation and Productivity: An Econometric Analysis at the Firm Level", *Economics of Innovation and New Technology*, Vol. 7(2), 115-158.

Crespi G., Tacsir, E. and Vargas, F. (2016). "Innovation Dynamics and productivity: Evidence for Latin America" in Grazzi, M. and Pietrobelli, C. (eds) *Firm innovation and productivity in Latin America and the Caribbean: The Engine of Economic Development*. Washington: Inter-American Development Bank and New York: Palgrave Macmillan.

Crespi, G., & Zuniga, P. (2012). "Innovation and productivity: evidence from six Latin American countries". *World development*, Vol. 40(2), 273-290.

Disney, R., Haskel, J. and Heden, Y., (2003). "Restructuring and Productivity Growth in UK Manufacturing". *The Economic Journal*, Vol. 113(489), 666–694.

Dosi G. (1988). "Sources, Procedures, and Microeconomic Effects of Innovation". *Journal of Economic Literature*, Vol. 26(3), 1120-71.

Economic Commission for Latin America and the Caribbean (ECLAC) (2022). Innovation for development: the key to a transformative recovery in Latin America and the Caribbean. *LC/CCITIC.3/3*.

Figal Garone, L., López Villalba, P., Maffioli, A. and Ruzzier, C., (2020). "Firm-level productivity in Latin America and the Caribbean", *Research in Economics*, Vol. 74(2), 186-192.

Fiorentin, F., Suárez, D., and Yoguel, G. (2023). "Who benefits from innovation policy? The role of firms' capabilities in accessing public innovation funding". *Innovation and Development*, Vol. 13(1), 91-108.

Foster, L., Haltiwanger, J. and Syverson, C. (2008). "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?". *American Economic Review*, Vol. 98(1), 394-425.

Grazzi, M. and Pietrobelli, C. (2016). *Firm innovation and productivity in Latin America and the Caribbean: The Engine of Economic Development*.

Washington: Inter-American Development Bank and New York: Palgrave Macmillan.

Hsieh, C. and Klenow, P. (2009). "Misallocation and Manufacturing TFP in China and India," Quarterly Journal of Economics, 124 (4), 1403–1448.

Ito, K., and Lechevalier, S. (2009). "The Evolution of the Productivity Dispersion of Firms: A Reevaluation of its Determinants in the Case of Japan". *Review of World Economics*, Vol. 145(3), 405–429.

Lööf, H., Mairesse, J., & Mohnen, P. (2017). "CDM 20 years after". *Economics of Innovation and New Technology*, Vol. 26(1-2), 1-5.

Lundvall, B.Å. (1992). *National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning*. London: Pinter.

Molina-Domene, M, and Pietrobelli, C. (2012). "Drivers of technological capabilities in developing countries: An econometric analysis of Argentina, Brazil and Chile". *Structural Change and Economic Dynamics*, Vol. 23(4), 504-515.

Morris, D. (2018). "Innovation and productivity among heterogenous firms". *Research Policy*, Vol. 47(10), 1918-1932.

Navarro, J., Benavente, J. and Crespi, G. (2016). *The New Imperative of Innovation Policy: Perspectives for Latin America and the Caribbean. Policy Perspectives for Latin America and the Caribbean*. Inter-American Development Bank.

Nelson, R. (1991). "Why Do Firms Differ, and How Does It Matter?". *Strategic Journal of Management*, Vol. 12(S2), 61–74.

OECD (2023). *OECD Science, Technology and Innovation Outlook 2023: Enabling Transitions in Times of Disruption*, OECD Publishing, Paris.

Pagés, C. (2010). *The Age of Productivity: Transforming Economies from the Bottom Up*, Washington: Inter-American Development Bank and New York: Palgrave Macmillan.

Peres, W. and Primi, A. (2019). "Industrial Policy and Learning: Lessons from Latin America", in Oqubay, A. and Ohno, K. (eds), *How Nations Learn: Technological Learning, Industrial Policy, and Catch-up*. Oxford Academic.

Syverson C. (2004). "Product Substitutability and Productivity Dispersion". *Review of Economics and Statistics*, Vol. 86(2), 534–50.

Syverson C. (2011). "What Determines Productivity?". *Journal of Economic Literature*, Vol.49(2), 326–365.

United Nations (2023). *World Economic Situation and Prospects 2023*. New York: Department of Economic and Social Affairs.

Inventions, public subsidies and market launch: opportunities and limits of patenting support in Argentina

Invenciones, subsidios públicos y llegada al mercado: oportunidades y límites del apoyo al patentamiento en Argentina

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Carlos Aggio**
Vladimiro Verre***

Abstract

ANR Patentes is an Argentinean program that gives grants for patents applications to innovative firms, entrepreneurs and researchers. Throughout the period 2007-2017, 83 projects (out of 195) were funded. Based on secondary sources and a survey conducted to beneficiaries, this study reconstructs the progress made by the patent applicants. The results show, on the one hand, that a high percentage of the patents have been granted, and, on the other hand, a group of projects are facing difficulties to reach the market. Thus, the study suggests the necessity to complement ANR Patentes with other instruments oriented to foster entrepreneurship and productive development.

Key words: *Public subsidy, patent, market.*

JEL Classification: *O30 O32 O34.*

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Resumen

El ANR Patentes es un instrumento que otorga subsidios al patentamiento de desarrollos innovadores en Argentina. Entre 2007 y 2017 se financiaron 83 proyectos de 195 postulaciones. A partir de información secundaria y de una encuesta a beneficiarios se pudo reconstruir el camino de las solicitudes de patentes financiadas. Los resultados revelan una alta tasa de otorgamiento de las patentes solicitadas y, que un conjunto de proyectos ha enfrentado dificultades para llegar al mercado. Esto indica la conveniencia de articular este instrumento con programas orientados al emprendedurismo y con fuentes de financiamiento para el desarrollo productivo.

Palabras clave: *Subsidio público, patente, mercado.*

Clasificación JEL: *O30 O32 O34.*

1. Introduction

Promoting the protection and exploitation of the intellectual and industrial property (IP) of locally generated knowledge is part of the public agenda in many countries. This promotion is implemented in at least four ways (Xu and Munari, 2016): i) measures promoting patent-filings; ii) measures promoting patented technology maturation; iii) measures promoting patent exploitation; and iv) measures promoting patent leverage to access external financing. This paper focuses on an instrument called Aporte no Reembolsable Patentes (ANR Patentes), managed by the Argentine Technological Fund (FONTAR), which falls into the first category insofar as it finances the preparation and filing of patent applications (or utility models) in Argentina and elsewhere. Its ultimate purpose is to protect innovative results generated by the Argentinean scientific, technological and productive sector.

ANR Patentes differs from other programs in the world that provide patent fillings subsidies since there is a fairly rigorous selection and evaluation process of the beneficiaries before granting the funds. On the contrary, other countries such as Italy and mainly China, provide subsidies almost automatically based on the chronological order of applications after a check of formal requirements (Xu and Munari, 2016; Lei, et al, 2013). Due to its scale, these schemes have resulted in a rise of the aggregate number of patents in those countries but have raised concerns about the quality (measured by the number of forward citation and concession) and economic value (measured by economic performance after the subsidy) (Li, 2012; The Economist, 2010).

ANR Patentes partially covers expenses associated with the patent application of those projects that surpassed the instrument ex-ante evaluation. The subsequent results such as the actual granting of the patent and its commercial exploitation are beyond the scope and control of FONTAR. The program does not provide additional support to maintain the validity of the patent in the event that it is granted, nor for the investments required to transform the protected invention into an innovation. However, the instrument implicitly assumes that the stages following the application will be effectively carried out in all cases. In accordance with this expectation, subsidy candidates must demonstrate not only their product or process's "inventive step" to be deemed as patentable, but also its further commercial potential.

The objective of this paper is twofold. Firstly, it aims to make a methodological contribution to trace and evaluate the path followed by patent applicants after their requests. Secondly, it aims to find out what has happened to the patent applications financed by ANR Patentes. On the one hand, it verifies to what extent the projects assisted have effectively achieved market performance expectations. On the other hand, it analyzes those aspects of the instrument that could be reformulated to improve its functioning and expected results. In addition, given that this type of financing in other countries is given almost automatically to all applicants through large-scale programs, both the methodological strategy for gathering evidence and the results of Argentina's ANR Patentes constitute a contribution to the debate of how to evaluate small-scale and niche instruments.

The remainder of this paper is organized in four sections. The next section introduces the instrument under analysis in terms of its objectives, characteristics and general results. The third section develops the methodology used to collect information about the path followed by the applications financed by ANR Patentes after receiving the subsidy. The fourth section is devoted to presenting and analyzing the evidence generated. Finally, the fifth section is devoted to conclusions and policy recommendations derived from the study.

2. ANR Patentes in Argentina

ANR Patentes is a subsidy aimed at protecting R&D results by supporting the preparation and/or filing of invention and utility model patent applications.[1] The subsidy covers up to 80% of the project, up to USD 5,000 for applications in Argentina and USD 75,000 abroad. The maximum duration of projects is

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1 The translation of Aporte no Reembolsable (ANR) is non-refundable funding, but strictly speaking it is a subsidy.

36 months. It is aimed at: a) national SMEs; b) individuals; c) public and/or private non-profit scientific and technological institutions.

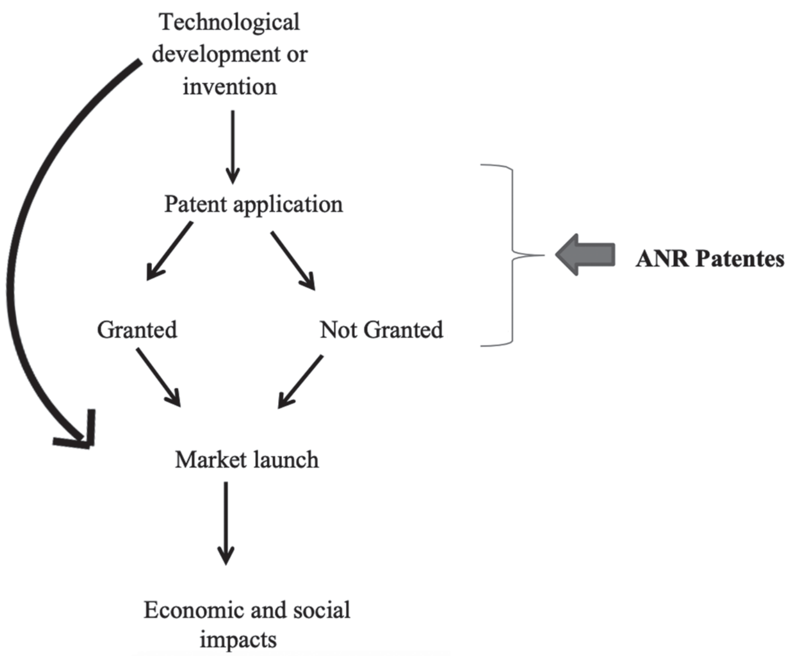
Diagram 1 shows a stylized illustration of a complete cycle of an innovative project and where ANR Patentes makes its contribution. It starts with a research and development phase that may be driven by the search for a technological solution to a problem and/or by the identification of a market opportunity. The duration of this stage varies according to the type and complexity of the project and in some cases it also receives public funding. When the results obtained are positive, the development or invention takes place. When this milestone is sufficiently inventive it becomes patentable in order to, among other things, prevent copying and/or generate income through the licensing of the patent.[2]

After that, regardless of whether or not a patent is granted, the innovation is completed when the development is taken to a productive scale, reaches the market and is commercially exploited. Finally, these projects can be associated with broader potential socioeconomic impacts in different aspects. In economic terms, the potential is to: i) increase productivity; ii) develop new (niche) markets, iii) substitute imports, iv) generate exports and/or new jobs, among others. Socially, these projects can potentially improve the quality of life of the population (for example, through health) and generate greater inclusion in disadvantaged or relatively less developed groups or regions of the country.

[2] The patent guarantees the private appropriation of the innovation through the exclusive rights granted to the inventor. At the same time, it allows a certain diffusion of knowledge by requiring the description of the invention or development to be made public (Griliches, 1990). Several studies show that patents are more widely used to protect product innovations than process innovations and, that their use and effectiveness vary according to the industrial sector (Mansfield, 1986; Levin et al., 1987). Among the limitations of this instrument are the difficulty in demonstrating the novelty of the invention, the disclosure of information to potential competitors and the high costs of application and defense (Levin et al., 1987; Cohen et al., 2000).

DIAGRAM 1

INNOVATIVE PROJECT CYCLE AND ANR PATENTES' CONTRIBUTION



Source: Own elaboration based on Verre et al (2020).

ANR Patentes funding is conditioned by three evaluation stages: (i) a patentability analysis, conducted by evaluators based on a state-of-the-art search provided by the applicant; (ii) an economic feasibility analysis that includes, at least, a forecast of the potential economic impact, market profile and the capacity of the holder to scale up the project, using the idea commercially or licensing the invention. As part of this, the correspondence between the export strategy, market opportunities and countries in which the patent application is intended is also evaluated; (iii) the financial capacity of the applicant to cover the counterpart contributions foreseen by the instrument.

The main eligible expenses include the fees associated with the preparation and submission of the application (drafting, preparation of drawings and figures, translations, compliance with standards and preparation of supplementary documentation required by the various offices, etc.) and the respective fees and tariffs.

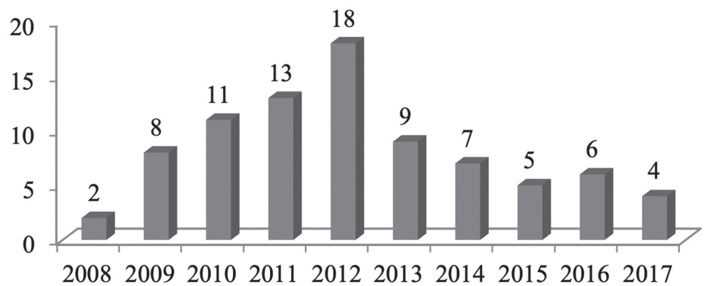
Finally, it should be noted that, as can be seen from the economic viability analysis that includes the evaluation of projects, the spirit of the instrument is not merely to increase the number of patents, but rather that the industrial property protection conferred by these patents should facilitate the development or invention to effectively take advantage of opportunities and meet needs, with a consequent socioeconomic and competitive impact from the knowledge generated.

Up to 2017, the instrument received 195 applications, of which 83 were financed. Some beneficiaries received funding for more than one project, so the total number of beneficiaries is lower than the number of projects. In this regard, there are a total of 58 beneficiaries of which 42 obtained funding for a single project and 16 obtained funding for two or more projects.

The annual evolution shows a steady growth until 2012 and then a decline until 2017 (Figure 1).

FIGURE 1

ANNUAL EVOLUTION OF THE NUMBER OF PROJECTS FINANCED

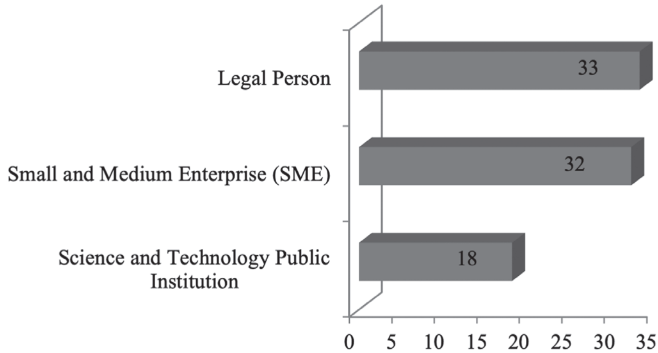


Source: Own elaboration based on information provided by FONTAR.

In terms of the types of beneficiaries, coinciding with the objectives of the instrument, legal persons and SMEs predominate, together accounting for 65 projects (78%), while public institutions were the beneficiaries of the remaining 18 (22%) (Figure 2). It should be noted that within this total, four public-private associative projects were also identified.

FIGURE 2

NUMBER OF PROJECTS FINANCED ACCORDING TO TYPE OF BENEFICIARY



Source: Own elaboration based on information provided by FONTAR.

The methodological approach and main results corresponding to the path followed by the patent applications of these 83 projects are presented below.

3. Methodology

The methodological strategy used to access information on the results of the projects was based on secondary and primary sources (see Table 1 for the coverage and type of information collected in each case).

TABLE 1

SUMMARY OF SOURCES, COVERAGE AND NATURE OF THE INFORMATION COLLECTED BY TYPE OF SOURCE

	Secondary	**Primary**
Source	Patent databases: • PatentScope • Google Patents • Espacenet	Survey of ANR Patentes beneficiaries
Coverage	83 projects (100%)	33 projects (40%)
Type of information obtained	Office(s) of application, status (granted, in force), record of other applications made by the beneficiaries.	
		Motivations and difficulties encountered in the application process. Commercial exploitation. Experience with the public sector.

Source: Own elaboration.

Secondary information on the status of applications was obtained from open access patent databases such as PatentScope, Google Patents and Espacenet. PatentScope, a search engine provided by the World Intellectual Property Organization (WIPO), was initially consulted to identify patent applications that met three conditions: 1) they included ANR beneficiaries as applicants; 2) they revealed lexical proximity to the respective project title; and 3) they were contemporaneous with the project in chronological terms. The PatentScope search was configured to include results from all offices while disabling the automatic separation of words into lexemes. Subsequently, for each of the applications retrieved from PatentScope, we proceeded to identify the "twin" records indexed by Google Patents that allowed us to incorporate the patent grant date. Since only entries in the national or regional phases following the Patent Cooperation Treaty (PCT) application are likely to be granted (or rejected), and this occurs according to the applicable law in each jurisdiction, in the case of applications made through the PCT, it was decided to assign the earliest grant date to the first entry at the national phases level. Cross-checking with Google Patents also made it possible to know whether granted patents are active or in force.

Likewise, in order to measure the relevance of ANR Patentes in the intellectual property management trajectory of the beneficiaries, patent applications made by the beneficiaries but not related to the financed projects were searched for and retrieved.

Finally, data cleaning was performed in terms of consistency and completeness and ex post filtering by categories and by automated identification/sorting strategies to remove duplications, outliers and anomalies from the database.

Regarding commercial exploitation and other aspects of the patenting process, a survey was conducted since such information is not available in the patent databases. The questionnaire contained five sections (see Table 2) and was managed through an online platform. As can be seen, in addition to the information on commercial exploitation, the questionnaire also asked about aspects captured by the patent databases, such as the application and granting process, both to allow the respondent to reference the subsequent questions and to corroborate the accuracy of the information obtained from the patent databases. Likewise, in each segment, qualitative aspects of the process, such as the reasons for patenting, were explored in depth. Finally, the beneficiaries were asked about their evaluation of the instrument and their general experience of the relationship with the Public Sector.

TABLE 2
MAIN SECTIONS OF THE QUESTIONNAIRE

Section title	**Type of information surveyed**
Basic data	Identifies the respondents and allows contact in case it is necessary to re-survey or validate any of the answers.
Information about the patent application(s)	General characteristics of the application: i) title of the invention, ii) year of application, iii) type of filing (PCT or not PCT), iv) countries where the application was initiated, iv) motivations for patenting.
Granting of patent(s)	Inquiry into the status of the application(s) made; that is, if it was granted or not in any of the offices where the application was made. In cases where it was not granted, the status of the process and the reasons for not obtaining the patent; in cases where it was granted, in which countries.
Transfer and/or arrival on the market	Aimed at finding out whether the development for which the patent was applied for is in any type of commercial use. Factors explaining the arrival or non-arrival to the market.
Experience with the Public Sector	We asked about the beneficiaries' links with other public programs and their assessment of their experience with the ANR Patentes instrument.

Source: Own elaboration.

The beneficiaries were contacted via an e-mail in which the objectives of the survey were explained. This was then reinforced with a telephone call. Consultation channels were also set up via e-mail and telephone in cases where beneficiaries had doubts or needed assistance in filling out the survey form. The field work was carried out during the month of November 2021 and complete responses for 33 of the 83 projects (40%) were obtained (Table 3). The non-probabilistic sample resulting from sending the form to all validated contacts has a composition by type of beneficiaries that has relatively minor differences with those of all projects. Public institutions are overrepresented and legal persons are slightly underrepresented.

TABLE 3
RESPONSE RATE BY TYPE OF BENEFICIARY

Type of beneficiary	Number of financed projects	Number of responses	Response rate
SME	31	12	39%
Legal Person	33	11	33%
S&T Public Institution	19	10	53%
Total	83	33	40%

Source: Own elaboration.

The results obtained are presented below. In cases where the information is derived from patent databases, it refers to the total of 83 projects, while results refer to the 33 projects for which complete responses were obtained. The combination of information gathered from these two sources allowed us to check the status of patent applications and to extrapolate the commercial exploitation of those patents to the universe of financed projects.

4. Results

4.1 Patent Applications

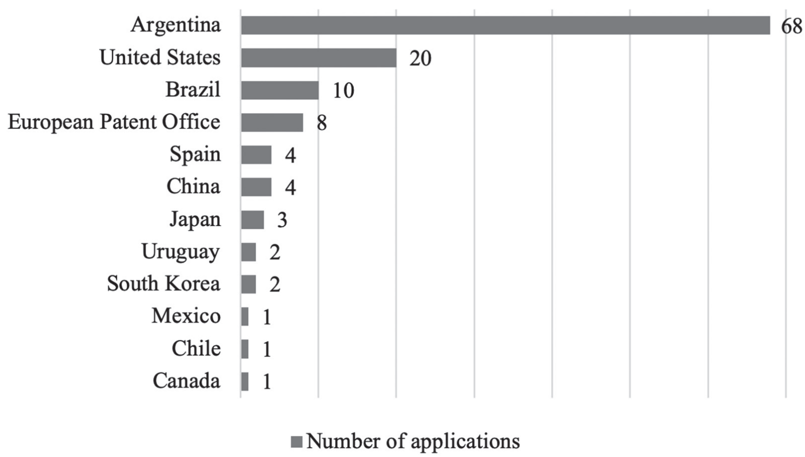
All of the projects (100%) met the objective of filing patent applications: 124 applications were made in national offices (some projects resulted in more than one application), while 42 applications were made through the PCT system, at an average of 1.49 and 0.51 applications per project respectively. By contrast, among non-beneficiaries, only 30% of SMEs and legal persons and only 40% of science and technology public institutions applied for the patent for which they had applied to the ANR.

The next figure shows that among applications to national offices, those filed in Argentina predominate, followed by those filed in the United States. In the case of the PCT, the largest number of filings was made at the WIPO and the Spanish office. It should be noted that PCT applications cannot be filed at the Argentine office since the country has not signed the agreement.

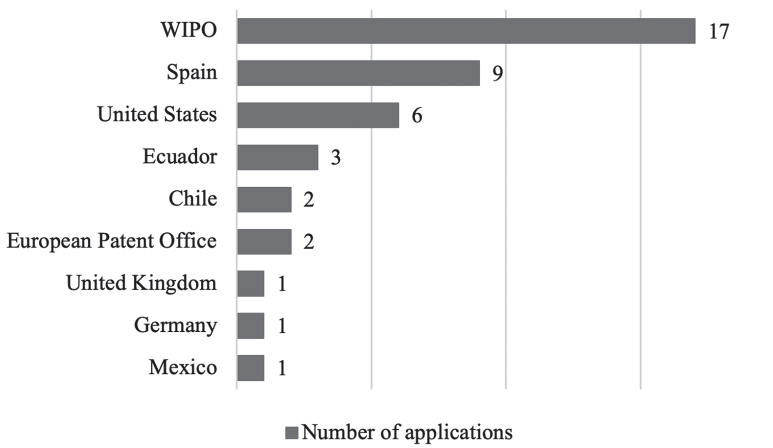
FIGURE 3

NUMBER OF PCT AND NON-PCT PATENT APPLICATIONS BY OFFICE OF ENTRY

A. NON-PCT



B. PCT

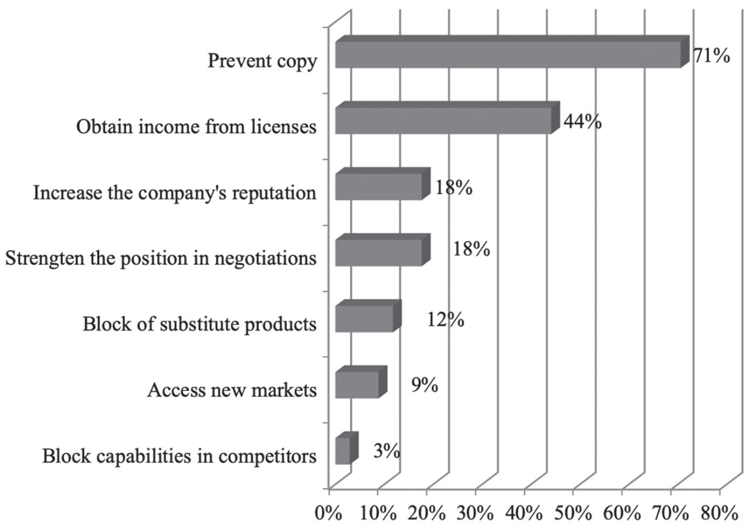


Source: Own elaboration based on information from PatentScope.

In line with the international literature (Levin et al., 1987; Blind et al., 2006; Guiri et al., 2006; Blind et al., 2009; De Rassenfosse, 2012; Holgersson and Granstrand, 2017), the main motivation for patenting is to prevent copying

(70%). However, again in line with the literature, other motivations related to what is called strategic patenting also have significant percentages. Among them, obtaining licensing income (44%) and, to a lesser extent, improving reputation (18%) and strengthening a negotiating position (18%) stand out. Blocking substitutes or competitors, which for instance appear as important strategic motivations when analyzing the most recent Argentine innovation survey, ENDEI II (Petelski et al., 2020), are less important in this case[3], supporting the objectives of the instrument to increase patenting, and validating, in accordance with this, the type of agents targeted by the instrument.

FIGURE 4
MAIN MOTIVATIONS FOR FILING A PATENT APPLICATION
(% OF RESPONSES RECEIVED)



Notes: Respondents could answer more than one option.
Source: Own elaboration based on survey to beneficiaries of ANR Patentes.

Finally, regarding the technological field of the applications, Table 4 shows that although they are varied, since they are distributed among 7 of the 8 sections of the International Patent Classification (IPC), 83% are concentrated in

[3] The correlation index between the ranking of motivations of ANR beneficiaries and ENDEI II patenting companies is low (0.21), with a relative preeminence of the use of the patent (whether internal or by licensing) in the first case and of the blockage in the second case.

four sections (A, B, C and G). In terms of classes, the applications are distributed among 36 of the 130 IPC classes[4].

TABLE 4
DISTRIBUTION OF APPLICATIONS BY IPC SECTIONS AND CLASSES

Code	**Description**	**Part.**
A	**Human necessities**	**28%**
A61	Medical or veterinary sciences; hygiene	12%
A01	Agriculture; forestry; animal husbandry; hunting; trapping; fishing	7%
A47	Furniture; domestic articles or appliances; coffee mills; spice mills; suction cleaners in general	4%
A41	Wearing apparel	3%
A23	Foods or foodstuffs; treatment thereof, not covered by other classes	1%
A62	Life-saving; fire-fighting	1%
B	**Performing operations; transporting**	**21%**
B63	Ships or other waterborne vessels; related equipment	5%
B60	Vehicles in general	4%
B65	Conveying; packing; storing; handling thin or filamentary material	3%
B01	Physical or chemical processes or apparatus in general	2%
B23	Machine tools; metal-working not otherwise provided for	2%
B66	Hoisting; lifting; hauling	2%
B62	Land vehicles for travelling otherwise than on rails	1%

4 The IPC is composed of sections, classes, subclasses, groups and subgroups that in the 2015 version reached 8, 130, 639, 7402, 64332 respectively (see https://www.inegi.org.mx/contenidos/app/scian/cip.pdf). The information on applications funded by ANR Patentes is registered at the subgroup level. However, for stylization purposes version reached 8, 130, 639, 7402, 64332 respectively (see https://www.inegi.org.mx/contenidos/app/scian/cip.pdf). The information on applications funded by ANR Patentes is registered at the subgroup level. However, for stylization purposes, we decided to group them by sections and classes, taking the first subgroup indicated in each application, which in many cases are multiple, reaching 16 in some of them. In this sense, this exercise is a very imprecise approximation since not in all offices the first code is the most important one. See in this regard OECD (2009). However, it should also be noted that almost all applications financed by the ANR Patentes that present more than one IPC code do so within the same section and in many cases also within the same class.

B29	Working of plastics; working of substances in a plastic state in general	1%
B32	Layered products	1%
C	**Chemistry; metallurgy**	**21%**
C12	Biochemistry; beer; spirits; wine; vinegar; microbiology; enzymology; mutation or genetic engineering	8%
C07	Organic chemistry	5%
C02	Treatment of water, waste water, sewage, or sludge	4%
C01	Inorganic chemistry	2%
C04	Cements; concrete; artificial stone; ceramics; refractories	1%
C11	Animal or vegetable oils, fats, fatty substances or waxes; fatty acids therefrom; detergents; candles	1%
G	**Physics**	**13%**
G06	Computing; calculating or counting	5%
G01	Measuring; testing	3%
G02	Optics	2%
G07	Checking-devices	1%
G21	Nuclear physics; nuclear engineering	1%
G09	Educating; cryptography; display; advertising; seals	1%
E	**Fixed constructions**	**7%**
E04	Building	4%
E21	Earth or rock drilling; mining	2%
E01	Construction of roads, railways, or bridges	1%
F	**Mechanical engineering; lighting; heating; weapons; blasting**	**7%**
F16	Engineering elements or units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general	4%
F24	Heating; ranges; ventilating	1%
F28	Heat exchange in general	1%
F03	Machines or engines for liquids; wind, spring, or weight motors; producing mechanical power or a reactive propulsive thrust, not otherwise provided for	1%
F04	Positive-displacement machines for liquids; pumps for liquids or elastic fluids	1%
H	**Electricity**	**4%**
H04	Electric communication technique	2%
H01	Basic electric elements	1%

Source: Own elaboration based on information from PatentScope and OECD (2009).

4.2 Patents Granted

In terms of patents granted, 76% of the projects (63 out of 83) were granted at least one of the patents applied for, indicating that the selection of projects has adequately foreseen the potential for patentability in most cases. This conclusion is reinforced if we analyze the reasons in the six surveyed cases of non-granting. Within these cases, there are two that are still in the process of analysis (filed in 2016 and 2017) and could end up being granted. Of the remaining four, in three projects, the inventors desisted from continuing with the process, and in one case, the patent was formally denied by the European Patent Office for lack of an inventive step[5].

The 63 projects that were granted patents generated a total of 166 applications and 83 patents granted, 62 by direct entry to national offices (50% of applications) and 21 by entry through the PCT system (50% of applications). Of this total, 66 are still in force (46 and 20, respectively). Table 5 summarizes this information.

TABLE 5

PATENTS APPLICATIONS, GRANTS AND IN FORCE

Project results	Number	Average per project
National Offices		
Applications		1.49
Grants		0.75
Grants/Applications (in %)	50.0	
In force		0.55
In force/Grants (in %)	74.2	
PCT		
Applications	42	0.51
Grants		0.25
Grants/Applications (in %)	50.0	
In force		0.24
In force/Grants (in %)	95.2	

Source: Own elaboration based on information from the ANR PATENTES Database, PatentScope, Espacenet and Google Patents.

5 In this case, however, the holder registered the invention as a utility model in Spain.

Some characteristics of applicants and applications affect the probability of obtaining the patent. Table 6 shows how the applications are distributed (taking the total of 166 applications) between granted and not granted according, on the one hand, to the type of applicant and their previous experience in patent applications and, on the other, to the application office and the technological class (at the section level). As can be seen, those beneficiaries with prior experience and who are SMEs or science and technology institutions show a higher proportion of patents granted than those who are legal persons and have no experience, respectively. For their part, the application offices with the highest proportion of patents granted are the USPTO and those in Asian countries, while those with the lowest proportion of grants are those filed in neighboring countries. Finally, the technological classes with the highest proportion of concessions are B (mainly related to machines, devices and transportation equipment for various activities) and E (mainly related to transportation, water and mining infrastructure).

TABLE 6

GRANTED APPLICATIONS ACCORDING TO CHARACTERISTICS OF APPLICANTS AND APPLICATIONS

Characteristics	Results of Patent Applications					
	Number			Percentage		
	Not granted	Granted	Total	Not granted	Granted	Total
Type of beneficiary						
Legal person	40	31	71	56%	44%	100%
SME	26	31	57	46%	54%	100%
S&T public institution	17	21	38	45%	55%	100%
Total	83	83	166	50%	50%	100%
Previous experience applying to patents						
No	48	39	87	55%	45%	100%
Yes	35	44	79	44%	56%	100%
Total	83	83	166	50%	50%	100%
Office of application						
AR	33	35	68	49%	51%	100%
PCT	21	21	42	50%	50%	100%
USPTO	8	12	20	40%	60%	100%
Other South American countries (Brazil/Chile/Uruguay)	16	0	16	100%	0%	100%
Asian countries (China/S. Korea/Japan)	2	11	13	15%	85%	100%
Other Countries/Offices	3	4	7	43%	57%	100%
Total	83	83	166	50%	50%	100%
International Patent Class (Sections)						
A (Human necessities)	25	22	47	53%	47%	100%
B (Performing operations, Transporting)	12	22	34	35%	65%	100%
C (Chemistry; Metallurgy)	20	13	33	61%	39%	100%
D (Textiles; Paper)	0	0	0	-	-	-
E (Fixed constructions)	4	8	12	33%	67%	100%
F (Mechanical engineering)	7	5	12	58%	42%	100%
G (Physics)	10	12	22	45%	55%	100%
H (Electricity)	5	1	6	83%	17%	100%
Total	83	83	166	50%	50%	100%

Source: Own elaboration based on information from the ANR PATENTES Database, PatentScope, Espacenet and Google Patents.

Some of these effects remain and others disappear when a probit model of the probability of obtaining the patent is estimated. In this case, each of the characteristics in Table 7 are included as dummies and an indicator of the number of years since the request is added to control for biases associated with the non-granting of the most recent applications. However, the average elapsed time is around 10 years, for both granted and not granted applications.

TABLE 7

DETERMINANTS OF THE PROBABILITY OF OBTAINING THE PATENT

Explanatory variables	**F=Pr(Grant=1)**
SME	0.421*
S&T public institution	0.433
Experience	0.170
AR	0.393
PCT	0.437
USPTO	0.811
Other South American	-0.790
Asia	1.482*
IPC_A	4.062
IPC_B	4.788
IPC_C	3.876
IPC_E	4.671
IPC_F	4.555
IPC_G	4.318
IPC_H	3.147
Time	0.144***
Constant	-6.431
Observations	166
Pseudo R2	0.2031

*** p<0.01, ** p<0.05, * p<0.1

In the multivariate framework, the probability of obtaining increases when the beneficiary is an SME, when the application is made in Asian offices and also increases as more time passes from the moment of the application (Table 7).

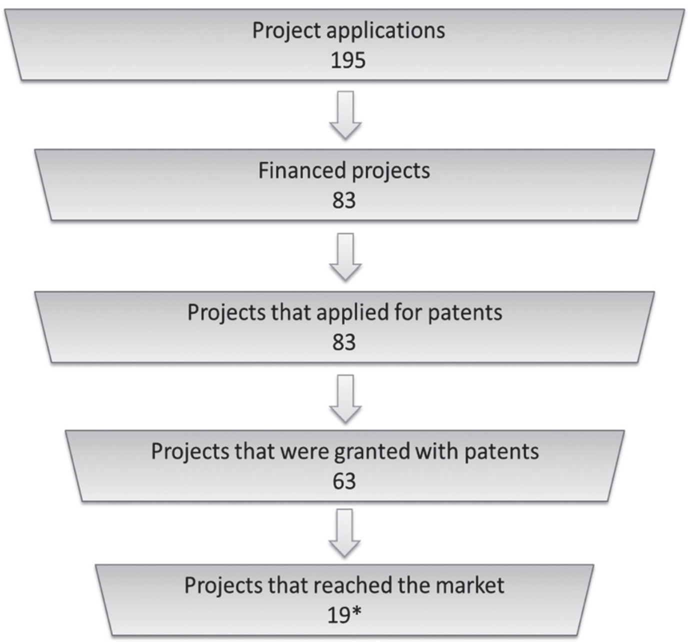
4.3 Commercial Exploitation

Finally, with regard to commercial exploitation, which is the most difficult information to reconstruct from secondary sources, the results of the fieldwork show that almost one third of the projects (10) reached this phase, 70% of them directly and 30% through licensing. If these proportions are extrapolated directly to the total number of projects that obtained patents, it would mean that 19 of the 63 would be exploiting the patent, 14 of them directly and the remaining 5 through licensing.

All of the above shows that for various reasons, there are some projects that fall along the way from project presentation to market arrival. This can be seen graphically in the following diagram.

DIAGRAM 2

PROJECT PATHWAY BETWEEN APPLICATION AND ARRIVAL TO MARKET



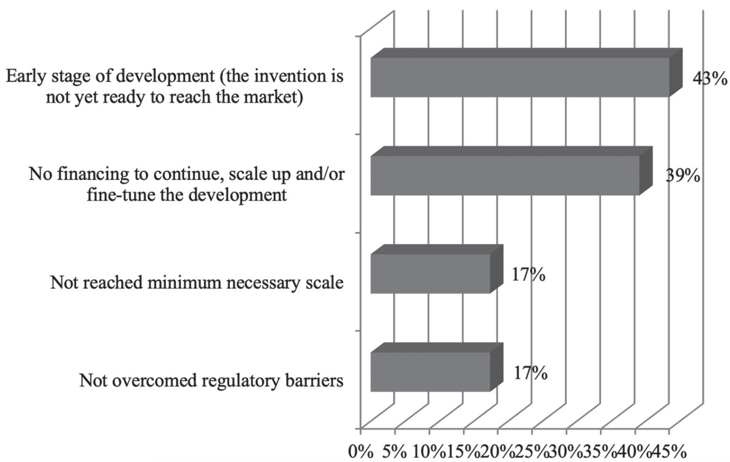
*Estimated based on Survey to beneficiaries of ANR Patentes.

Source: Own elaboration based on information provided by FONTAR, ANR Patentes Database and survey of beneficiaries of ANR Patentes.

Regarding the projects that have not reached commercial exploitation, the reasons are varied. In 43% of the cases, the projects are still at an early stage of development to convert the invention into an innovation. If all of them were to reach commercial exploitation after completing the development phase, the percentage of patents that complete the cycle from application to market would double (43% of the 44 that have not reached the market). In the other cases, the constraints seem to be more definitive in that they refer to systemic conditions such as lack of financing (39%) and regulatory barriers (17%) or conditions intrinsic to the beneficiaries or the project itself that are very difficult to remove, such as lack of scale (17%).

FIGURE 5

MAIN REASONS FOR NOT BEING ABLE TO COMMERCIALLY EXPLOIT THE INNOVATIVE DEVELOPMENT (% OF PROJECTS THAT ARE NOT BEING EXPLOITED).



Note: Respondents could answer more than one option.

Source: Own elaboration based on survey to beneficiaries of ANR Patentes.

In this regard, the beneficiaries were asked about those aspects in which the public sector could have assisted the project to make it possible or to facilitate its arrival on the market. Of the 25 responses obtained, one main issue stands out: the fact that the invention still has some way to go before it can be exploited. There is a high proportion of projects that are still in the development phase, for example in the biotechnology area, and this is indicated as the main reason for non- exploitation, however, in these cases the question of the financing necessary for the projects to advance to a higher stage of development is implicit. This aspect is partially linked to another, which also emerged from the open-ended questions answered by the beneficiaries: the relationship with potential licensees. On the one hand, some beneficiaries mentioned that the potential licensee demanded the project show a higher degree of progress in order for them to get involved and invest, confirming the lack of maturity of the project to be an obstacle for its commercial exploitation. On the other hand, some potential licensees consulted found the cost/benefit ratio insufficient to undertake production or lacked the necessary production capacity to do so, which may indicate the need for greater activity in the promotion and dissemination of inventions so that supply and demand can meet. Among the other issues mentioned, the lack of articulation with other public institutions (the National Atomic Energy Commission – CNEA, the National Institute of Industrial Technology – INTI) that could have supported the projects from the technical point of view and the lack of regulatory support policies for the invention (the Argentine position towards the International Maritime Organization, the policy of the Secretariat of Energy on biodiesel, delays on the part of the National Administration of Drugs, Food and Medical Technology – ANMAT, among others) also stand out.

An additional element to consider regarding the general relevance of the instrument and its results is related to its role within the industrial property management trajectories of the beneficiary entities.

TABLE 8

PATENTING BEFORE AND AFTER ANR PATENTES

Beneficiary Entities	No previous or subsequent applications	Subsequent applications only	Previous applications only	Pre- and post-applications
SMEs	50%	8%	29%	13%
Legal persons	70%	4%	26%	0%
Institutions	20%	0%	0%	80%
Totals	56%			13%

Source: Own elaboration based on information from the ANR Patentes Database.

Of the total number of beneficiary entities, slightly more than half (56%) do not register patent applications before or after the ANR (Table 8). For these entities, it could be considered that, up until now, the ANR is an isolated milestone in their IP management. The highest proportion of beneficiaries in this condition corresponds to legal persons, where it reaches 70%, followed by SMEs (50%) and public institutions (20%). In this regard, when evaluating the instrument in the framework of the survey, several beneficiaries stated that without the instrument's support they would not have considered patenting their invention.[6] It remains to be seen whether, over time, some of these cases may also show that the ANR has been a learning milestone that mobilized their systematic IP management. For the moment, the evidence in this regard is scarce since only 6% of the beneficiaries, all of them SMEs and legal persons, reapplied for a patent after their first experience financed by ANR.

For another 25% of the beneficiaries – again made up exclusively of SMEs and legal persons – who already had prior application experience, the ANR has helped to finance their most recent application. Finally, for the remaining 13% with previous and subsequent patent application experience, the ANR appears to have been a funding opportunity for one-off applications in the framework of more established IP management. In this group, public institutions stand out in relative terms.

5. Conclusions and Recommendations

The evidence generated and analyzed in this study allows us to draw a set of reflections and conclusions about the policy instrument.

ANR Patentes has proven to be effective in its objective of supporting individuals, institutions and companies to protect intellectual property generated in the country. The evidence shows that three quarters of the projects financed have obtained at least one patent. In turn, considering averages, two patents were applied for per project and one was obtained. The survey reveals a generalized opinion among the beneficiaries that, without the instrument, it would have been difficult for them to patent, i.e., the subsidy was the condition for the possibility of patenting (project additionality) (Georghiou, 2002; Verre et al, 2020, Buisseret et al, 1995). To this is added an 'additionality of scale and scope' insofar as the subsidy has made it possible to expand the target countries in which to patent the invention (which would have been much smaller without public aid).

If we consider the different stages of the projects' life cycles (from the time they apply to FONTAR to obtain financing to commercial exploitation), a process of disengagement is observed. In the case of the most original evidence provided by this study, which corresponds to the step from obtaining the patent to reaching the market, a success rate of around 30% is observed – although

6 This statement seems to be confirmed by the results commented above. Only 40% of non-beneficiary public science and technology institutions applied for a patent, a percentage that drops to 30% in the case of SMEs and legal persons.

this may increase when the projects that are still at an early stage of their development reach commercial exploitation. In this step, there is a need to think of strategies to extend the support for projects in order to improve their chances of making an effective contribution to society through the commercial exploitation of patented inventions. Currently, this phase is not contemplated in ANR Patentes, but it is an instance whose concretion is crucial to give real meaning to the effort involved in supporting the patenting of inventions.

This entails the consideration of patenting as part of the innovation process, avoiding the patent becoming an end in itself, and pursuing the goal of reaching the market. To this end, it is suggested that two fundamental issues be addressed. Firstly, the evaluation of support mechanisms and/or actions to continue with the maturation process of the patented invention (development, prototyping, manufacturing, regulatory approval, etc.). Secondly, facilitation of the encounter between supply and demand for inventions. The former entails a need to articulate ANR Patentes with: i) instruments for other phases of the innovation process, ii) programs aimed at entrepreneurship, iii) sources of financing for productive development and iv) support for regulatory aspects (a need detected in several of the projects). A niche instrument, with a demanding ex-ante evaluation, would increae its impact as long as subsequent support to reach the market is also provided. The latter involves generating spaces and instances to guarantee the proper dissemination of inventions and potential licensees. A small-scale instrument, where 60% of beneficiaries are legal persons or public institutions, would benefit from the identification of a bank of potential licensees, which could strengthen the selection phase and facilitate the market exploitation. In this regard, it should be noted that the vast majority of the beneficiaries have not had access to other public support instruments, so there is an important space for articulating this instrument with others, based on a path that leads from the project idea to its application.

References

Blind, K., Edler, J., Frietsch, R., and Schmoch, U. (2006). "Motives to patent: Empirical evidence from Germany". *Research Policy*, 35(5), 655-672.

Blind, K., Cremers, K., and Mueller, E. (2009). "The influence of strategic patenting on companies' patent portfolios". *Research Policy*, 38(2), 428-436.

Buisseret, T., Cameron, H. and Georghiou, L. (1995) "What difference does it make? Additionality in the public support of R&D in large firms". *International Journal of Technology Management*, 10 (4/5/6), 587-600

Cohen, W., Nelson, R. and Walsh, J. (2000) "Protecting Their Intellectual

Assets: Appropriability Conditions and Why Us Manufacturing Firms Patent (or Not)", *Cambridge (MA): National Bureau of Economic Research*.

De Rassenfosse, G. (2012). "How SMEs exploit their intellectual property assets: evidence from survey data". *Small Business Economics*, 39(2), 437-452.

Georghiou, L. (2002). "Impact and Additionality of Innovation Policy", *Innovation Policy and Sustainable Development*, IWT Studies, 40, 57-65.

Giuri, P., Mariani, M., Brusoni, S., Crespi, G., Francoz, D., Gambardella, A and Verspagen, B. (2006). "Everything you always wanted to know about inventors (but never asked): Evidence from the PatVal-EU survey". Centre for Economic Policy Research.

Griliches, Z. (1990), "Patent Statistics as Economic Indicators: A Survey". *Journal of Economic Literature*, 28(4), 1661-1707.

Holgersson, M. and Grandstrand, O. (2017), "Patenting motives, technology strategies, and open innovation", *Management Decision*, 55(6), 1265-1284.

Lei Z, Sun Z, Wright B (2013) Are Chinese patent applications politically driven? "Evidence from China's domestic patent applications. Fung Institute Berkley Innovation Seminar paper" (downloaded on 10 Sep 2023 from https://www.oecd.org/site/stipatents/4-3-Lei-Sun-Wright.pdf)

Levin, R., Klevorick, A., Nelson, R., Winter, S., Gilbert, R. and Griliches, Z. (1987), "Appropriating the Returns from Industrial Research and Development", *Brookings Papers on Economic Activity*, v. 1987, n.3, 783-831.

Li, X (2012). "Behind the recent surge of Chinese patenting: an institutional view". *Research Policy*, 41 (1):236–249.

Mansfield, E. (1986), "Patents and Innovation: an empirical study". *Management Science*, 32(2): 173-181.

OECD (2009), OECD *Patent Statistics Manual*, OECD Publishing, Paris, https://doi.org/10.1787/9789264056442-en.

Petelski, N., Milesi, D. and Verre, V. (2020) "Patentamiento estratégico: rol de las patentes en las estrategias de las Pymes industriales argentinas", in Federico, J., Minetti, A., Rodriguez, M., Cahais, H. and Roitter, S. (eds) "Redes y conocimientos que impulsan la innovación y el desarrollo productivo y social", Asociación Civil Red Pymes, 480-493.

The Economist (2010) "Innovation in China: patents yes, ideas maybe". *The Economist*, 14 Oct.

Verre, V., Aggio, C., Milesi, D. and Lengyel, M. (2020). "Apoyo a la innovación:

reflexiones sobre el diseño y la evaluación de los fondos de innovación tecnológica sectorial", *Documento de Trabajo 18*, CIECTI.

Xu, L., and Munari, F. (2016). The impact of public support for SMEs' patenting activity: empirical evidence from Italy in Prud'homme, D. and Song, H. (eds) Economic impacts of intellectual property-conditioned government incentives, 101-131. DOI 10.1007/978-981-10-1119-1_4.

The Impact of Intangible Capital on Productivity and Wages: Firm level evidence from Peru*

El impacto del capital intangible en la productividad y los salarios: evidencia a nivel de empresas de Perú

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Abstract

In the past decades, intangibles assets have become an important source of productivity and economic growth in developed countries. Despite the transforming properties of intangibles across economies and the large and dynamic literature on the impact of intangible investments on productivity growth in frontier countries, there is not much evidence for the Latin America context. This paper contributes to the empirical literature on intangible investments along various dimensions. First, we make use of a large firm-level longitudinal data set from Peru, a Latin America middle income country, which contains separated information on intangible assets, which allow us to measure the impact of them on both wages and productivity at the firm level. Second, the analysis at the firm level and the panel structure of the data allows us to control for the endogeneity of variable inputs applying different control function approaches. In addition, the production function estimates provide us with a measure of unobservables, which we include in the wage equation to retrieve consistent estimates for the impact of intangible assets on wages. Third, our data allow us to explore how the impact of intangibles on wages and productivity is affected by the differences in the composition of the bundle of intangibles, changes in the product mix at the firm level and for the presence of imperfect competition in the labor market. We find that an increase in the share of intan-

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gible assets by one standard deviation is associated with 6.8% to 7.2% higher total factor productivity, depending on the model´s specification. We also find that the capital productivity premium of intangible assets over tangible ones is substantial with estimates suggesting that intangibles are up to 2 times more productive than tangible assets. We also find that this capital productivity premium is not entirely offset by an increase in wages. Finally, we conclude that the main channels for appropriability are the specificity of the ideas generated by intangible investments at the firm level and the wage compression due to imperfect competition in the labor market.

Key words: *Productivity; capital; intangible assets; production function; wages; innovation; R&D; firms; spillovers.*

JEL Classification: *D24, E22, O30, O47*

Resumen

En las últimas décadas, los activos intangibles se han convertido en una importante fuente de productividad y crecimiento económico en los países desarrollados. A pesar de las propiedades transformadoras de los intangibles en las economías y la amplia y dinámica literatura sobre el impacto de las inversiones en intangibles en el crecimiento de la productividad en los países más avanzados, no existe suficiente evidencia para el contexto de América Latina. Este estudio contribuye a la literatura empírica sobre inversiones en intangibles en varias dimensiones. Primero, hacemos uso de una amplia base de datos longitudinales a nivel de empresas de Perú, un país de ingreso medio de América Latina, la cual contiene información separada sobre activos intangibles, lo que nos permite medir el impacto de estos en los salarios y la productividad a nivel de empresa. Segundo, el análisis a nivel de empresa y la estructura de datos de panel nos permite controlar la endogeneidad de los insumos variables aplicando diferentes enfoques de funciones de control. Además, las estimaciones de la función de producción nos proporcionan una medida de las variables no observables, la cual incluimos en la ecuación salarial para obtener estimaciones consistentes del impacto de los activos intangibles en los salarios. Tercero, nuestros datos nos permiten explorar cómo el impacto de los intangibles en los salarios y la productividad se ve afectado por las diferencias en la composición del conjunto de intangibles, por cambios en el portafolio de productos a nivel de empresa y por la presencia de competencia imperfecta en el mercado laboral. Encontramos que un incremento de una desviación estándar en la participación de los activos intangibles se asocia con un aumento del 6.8% al 7.2% en la productividad total de los factores, dependiendo de la especificación del modelo. También encontramos que la prima de productividad del capital de los activos intangibles sobre los tangibles es sustancial, con estimaciones que sugieren que los activos intangibles son *hasta 2 veces más productivos que los activos tangibles. Además, encontramos que esta prima de productividad del capital no se compensa completamente con un aumento en los salarios. Finalmente, concluimos que los principales canales para la apropiabilidad son la especificidad de las ideas generadas por las inversiones intangibles a nivel de empresa y la compresión salarial debido a la competencia imperfecta en el mercado laboral.*

Palabras clave: *Productividad, Capital, Activos intangibles, Función de producción, Salarios, Innovación, I+D, Empresas, Externalidades.*

Clasificación JEL: *D24, E22, O30, O47.*

1. Introduction

One important feature of modern economies is the presence of a large and growing gap between tangible assets as reported in corporate annual reports and companies' market values. For example, the ratio between the market value and the accounted value of tangible assets – such as buildings and equipment – in the case of Apple and Microsoft is 5.9 and 7.3 times respectively (Corrado, Haskel, Jona-Lasinio, and Iommi, 2022). However, this gap cannot be explained only by capitalized research and development (R&D). Capitalizing R&D for Apple and Microsoft, reduces the gaps to just 4.9 and 5.2 times respectively. There is a remaining value gap that is explained by other types of knowledge investments that firms do and are not classified as R&D such as software, designs, branding, marketing, business practices, services delivery, after-sale services, and others. These other expenditures should be also considered as investments to the extent that are outlays expected to yield a return in the future. Recent research on national accounts suggests that once these intangible assets are computed as part of domestic gross investment a very different pattern emerges. Indeed, in the US, while tangible (fixed) capital investment drops from about 12.5% of the GDP in 1985 to about 8.5% in 2021, intangible capital investment rises rather dramatically from 4% to 16% of the GDP over the same period. Similar figures are reported in several EU countries (Corrado, Hulten, and Sichel (2005, 2009)). In summary, the global economy has entered into the *age of intangibles*, and it is expected that sooner rather than later similar patterns will be observed also in some Latin American countries.

Investment in intangible assets is basically foregone consumption in the accumulation of ideas, and ideas, unlike physical goods, have some particular properties. First of all, ideas are non-rivals in consumption. This is in the sense that a new idea, once developed, can be used without physical limits in numerous applications both inside and outside the generating firm. The second property of ideas has to do with their control. Ideas don't float around in the air, but generally tend to be associated for use with some kind of physical platform. For example, a chemical formula may be reflected in an article in a journal or in a patent document. A programming code can be written in a copyright document and a dataset can be stored in an external disk. An organizational routine can be compiled into a set of organizational policies sanctioned by a board of shareholders. In all these cases, the generating firm can regulate the access to these ideas by third parties by controlling the physical support on which these ideas are represented, such as when intellectual property rights as patents or copyrights mentioned above are generated. However, it is also true that on numerous occasions the physical support on which the idea is materialized is much more difficult to control. This is particularly the case when new ideas basically rest in the brains of the firm's workers who have participated in their generation and/or internal use. In this case, although there are control procedures such as confidentiality agreements, they are more difficult to implement and as such the human capital of the originating company becomes a physical backup whose control is much more difficult to exercise. In other words, one is certain that an engineer involved in research and development, design or value-chain optimization activities was in the company's floor today, but it is much more difficult to predict whether she will show up for work tomorrow and even more uncertain if she is not going to do it in some rival competitor firm. In short, the ideas that underlie investments in intangible assets are not only non-rivals in consumption, but also suffer from a problem of partial appropriability, particularly when this idea is only attached to the firm's human capital (Romer, 1989). These two characteristics of ideas generate knowledge externalities in the economy, but at the same time they might represent a disincentive to private investment in their generation[1].

[1] There is an emerging literature emphasizing on other characteristics of intangible assets that are beyond the aim of this paper. Indeed, according to Haskel and Westlake (2018), intangible investment has other three characteristics that differentiate it from tangible assets. *First*, an intangible investment is normally sunk, that means, it is a sort of investment that cannot be easily recovered after disbursed; *second*, an intangible investment is easily scaled up after the initial outlay (e.g. the fast growth of Uber after the initial software was developed) and *third*, an intangible investment normally has strong synergies and complementarities with other intangible investments. These three key characteristics have important policy implications. Being a sunk investment normally implies some difficulty to obtain external financing, scalability means that intangible-intensive companies get large very quickly implying competition worries and finally, the presence of synergies impact inequality to the extent that there are potentially large income gains for intangible capital owners. In summary, the rise of intangibles might lead to fast growing economies, if some market failures related to financing and spillovers are tackled, but also to more unequal societies due to the scaling and synergy properties.

However, one way the firm can increase the chances to appropriate the returns of the ideas is by focusing human capital related intangibles on those ideas which are more specific to firm's needs. Ideas that are rather generic in nature and that are difficult to protect using other methods such as intellectual property rights or by exploiting their complementarity with other firms' specific assets such as organizational routines or value chains, are far more likely to spillover to other firms via labor mobility. The presence of intangible assets embedded in human capital can also make appropriability dependent on the degree of competition in the labor market. If the firm enjoys some degree of market power in the labor market could also retain at least part of the returns to intangible assets, even in the case of generic knowledge. In other words, under perfect competition in the labor market firms won't pay for the development of generic ideas that are embedded in their workers who can leave the firm for a better-paid job that compensates them for the higher marginal productivity they obtain thanks to their access to those ideas. The only way a firm might be willing to invest in low appropriability generic ideas is if there is some form of compressed wage structure in the labor market through which marginal productivity increases more than wages.

Nevertheless, it is important to keep in mind that intangible assets bundle different components, in which the importance of non-rivalry and control is expected to vary across them. There is widespread consensus that R&D investments generate spillovers from the innovator to potentially rival firms (Hall, Mairesse and Mohnen, 2010). However, the extent to which the potential for knowledge spillovers also extends to other intangibles such as investments in business models, marketing, software, databases, and designs (among other assets) is more uncertain. Some researchers claim that these other intangibles are more tacit and linked to tangible capital investments rather than R&D, suggesting that their returns are more appropriable and so that spillovers might be lower. In fact, studies suggest that the productivity slowdown of the last couple of decades could be explained by the increasing share of these other intangibles vis-à-vis R&D (Haskel and Westlake, 2018). Whether these other intangibles should be subsidized is an empirical fact that is just starting to be tackled as more comprehensive and harmonized data regarding intangibles investments is being collected at the firm level. However, most of this research is still at early stages and mostly focused on the US and EU countries. Indeed, despite the transforming properties of intangibles across the economy, very little is known regarding the impacts of intangible investments in developing countries. A major constraint for this lack of evidence has been the absence of systematic firm level data on intangible capital and investment.

This paper contributes to the empirical literature on intangible investments along various dimensions. First, we make use of a large firm-level longitudinal data set that contains separated information on intangible assets, which allow us to measure the impact of them on both wages and productivity at the firm level. Furthermore, the data is from Peru, which is a Latin America middle income country so it could represent rather well the typical country in this region. Second, the analysis at the firm level and the panel structure of the data allows us to control for the endogeneity of variable inputs applying different control function approaches. In addition, the production function estimates provide us with a measure of unobserved productivity which we include in the wage equation to retrieve a consistent estimate for the impact of intangible assets on wages. Third, our data allow us to explore how the impact of intangibles depends on the composition of the bundle on intangibles and the product mix at the firm level.

We find that an increase in the share of intangible assets on total capital by one standard deviation is associated with 6.8% to 7.2% higher total factor productivity, depending on the model´s specification. We also find that the productivity premium of intangible assets over tangible ones is substantial with estimates suggesting that intangibles are up to 2 times more productive than tangible assets. However, consistent with the theoretical insights about partial appropriability of these investments, this capital productivity premium is not entirely offset by a similar increase in wages. The average wage per worker premium of intangibles is just a fraction of the capital productivity premium of intangibles. Finally, we conclude that the main channels for appropriability are the specificity of the ideas generated by intangible investments at the firm level and the wage compression due to imperfect competition in the labor market.

The paper is structured in the following sections after this introduction. In section 2 a literature review on the impact of intangible assets is carried out, including the main research questions emerging from it. Section 3 introduces the conceptual framework and section 4 outlines the estimation strategy. Section 5 describes the data after which the main results are presented in section 6. Section 7 introduces several extensions, while section 8 elaborates further on policy recommendations. Finally, section 9 closes the paper with the conclusion and recommendations for further research.

2. Literature Review

There is an important literature using growth accounting macro data to explore the contribution of intangibles to economic growth. This literature points out to the problems that exist to capitalize intangible investments trying to correct for several issues related to them such as the lack of price deflators or the uncertainty regarding their economic depreciation. Despite these concerns, the literature suggests that, under relatively reasonable assumptions, intangible assets accumulation has contributed half percent to labor productivity growth in Europe over the last two decades and even a little more in the case of the US (Corrado, et al., 2022). However, to the best of our knowledge, there is no similar evidence expanding national accounts for Latin American countries.

At the micro level, the empirical literature on intangible assets is not new. However, most of it focuses on the effects of particular types of intangibles. The most studied intangible so far is R&D. The literature on the returns (both social and private) to R&D has accumulated over half a century and it is mostly based on the use of a production function framework augmented by R&D[2]. Hall, et al. (2010) summarizes a large set of studies at the firm, industry, and country levels on the returns to R&D. When looking at the studies using firm level data, the major findings are that private returns to R&D are strongly positive and somewhat higher than those for ordinary capital[3]. In the case of Latin America, similar results have also been obtained for Chile (Benavente et al., 2005), but with evidence of important adjustment costs.

A more recent literature on R&D tackles the issue of spillovers which is important as R&D originated in one firm can affect the productivity performance of other firms. Most of the studies on spillovers have been conducted by adding a measurement of external (to the firm, sector, or country, depending on the level of aggregation) R&D to the production function. The empirical results suggest that spillovers are found to be positive and quite large, but rather imprecisely estimated[4]. More complex has been to identify the source or the channel through which spillovers materialize. One channel is researchers' labor mobility (Moen, 2005; Kerr, 2008 and Marilanta, et. al 2009), a second channel is knowledge diffusion among firms located within geographical clusters (Jaffe, 1989) and a final channel is through international spillovers (Coe and Helpman, 1995). Crespi et al. (2008) investigate spillovers by using direct measures of knowledge flows, as they are revealed by the UK Community Innovation Survey and find that flows from competitors, suppliers and plants

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2 More specifically, the residual factor in production that is not accounted by the usual inputs (labor, capital, intermediate materials) is assumed to be the product of R&D that produces technical change.

3 On the whole, although the studies are not fully comparable, it may be concluded that R&D rates of return in developed economies during the past half century have been strongly positive and may be as high as 75% or so, although they are more likely to be in the 20%-30% range (Hall, et al. 2010).

4 In principle spillovers can be also negative if there are market stealing effects. This is the case when a new product renders old products obsolete, when R&D is used strategically to preempt competition or when patent races lead to duplicative R&D. Bloom et.al. (2007) found evidence of market stealing effects for spillovers in the industry segment space as opposed to positive spillovers in the technology space.

that belong to the same group explain half of firm level total factor productivity growth. In this paper, information from competitors is considered to be pure knowledge spillovers. Spillovers can depend on the type of innovation, with product innovations having normally larger spillovers than process innovations (Ornaghi, 2006). In the case of Latin America, previous research has found significant and positive spillovers of R&D due to both researchers' labor mobility (Castillo, et.al., 2019) and geographical proximity, but in this case only for projects carried out in collaboration with universities (Crespi, et.al., 2020). However, the studies reviewed so far only apply to R&D which, according to national accounts estimates, is a rather small component of total intangible investments, and which economic properties cannot be linearly extrapolated to other intangibles.

With regards to other intangible assets, there is a very large but more recent literature regarding to the effects of information and communications technologies (ICT) capital on productivity. Using an ICT capital augmented production function, Bloom et al. (2012) find that US multinationals operating in Europe obtained higher productivity from ICT than non-US multinationals, particularly in the same sectors responsible for the US productivity acceleration. Furthermore, establishments taken over by US multinationals (but not by non-US multinationals) increased the productivity of their ICT capital afterwards. Combining European firm-level ICT data with a survey on management practices, they find that the US ICT capital productivity advantage is primarily due to its better management practices. Crespi, et al. (2007), examines the relationships between productivity growth, ICT investment and organizational change using UK firm panel data. Consistent with other micro studies, they find that ICT investment appears to have high returns in a growth accounting sense when organizational change is omitted; however, when organizational change is included ICT returns are greatly reduced, so ICT investment and organizational change interact in their effect on productivity growth. Finally, they also found that organizational change is affected by competition and the nationality of the owner of the firm. Consistently with Bloom et al. (2012), they found that US-owned firms are much more likely to introduce organizational change relative to foreign owned firms who are more likely still relative to UK firms. Baldwin and Sabourin (2002) examines the relationship between the use of ICT and growth in plant's market share and its relative productivity in Canadian Manufacturing, finding that technology users that were using communications technologies increased their relative productivity the most. Bresnahan et. al (2002) using US firm level data find evidence of complementarities between ICT, organizational change, and new products and services. In addition, firms that adopt these innovations tend to use more skilled labor. The effects of ICT on labor demand are greater when ICT is combined with organizational change. For Latin America, Aboal and Tacsir (2017), find that ICT play a bigger role for innovation and productivity in services than in manufacturing for the case of Uruguay. On the contrary, in the case of Peru and using firm level panel data, no clear effects of ICT on productivity are found (Garcia, 2022).

As for other intangibles, there is large empirical literature on the effects of training on productivity reporting mixed results mostly based on limited samples (Bartel, 1995; Black & Lynch, 2001; Zwick, 2006). For the remaining intangibles, the literature is scanter. One exception is Cereda et al. (2005) that analyses the relationship between design and economic performance by using the third wave of the UK Community Innovation Survey. By estimating a knowledge production function, an output production function, and a design expenditure function, they found that design expenditure also has a positive and statistically significant association with productivity with a return rate of about 20%.

With regards to the evidence of spillovers in the case of other intangibles, the literature is more limited. However, some related research on the productivity impacts of the mobility of key personnel at the firm level suggests that a partial appropriability scenario is the most likely result. For example, Van Reenen (1996) examines the impact of technological innovation on wages using a panel of British firms finding that innovating firms have higher wages, but rival innovation tend to depress own wages, a result which appears consistent with a model where wages are partially determined by a sharing in the rents generated by innovation. More recently, Kline et.al. (2018) link US patent application to US business and worker tax records, causally finding that an initial allowance of an ex-ante valuable patent generates substantial increases in firm productivity and in worker compensation suggesting that on average, workers capture roughly 30 cents of every dollar of patent-induced surplus in higher earnings. Some research makes use of event studies methodologies to assess the relevance of rent sharing of innovative rents. Research tracking executives' performance when they leave a company find that they are often unable of repeating their success, suggesting that the ideas are greatly appropriable at the firm level (Groysberg, McLean, and Nohria 2006). On the contrary, using administrative employer-employee matched data on US startups, Choi, et.al (2023) utilize premature death as a natural experiment that exogenously separates talent from startups. They find that losing an early joiner has large negative effects on employment and revenues that persist for at least ten years. In contrast, losing a later joiner yields only a small and temporary decline in firm performance. The results point to the fact that organizational capital, an important driver of start-up success, is embodied in early joiners. Regarding to the literature on training, Konings and Vormelingen (2015), use a Belgium firm-level panel data about on-the-job training to estimate its impact on productivity and wages. After correcting for the endogeneity of input factors and training, they found that the productivity premium of a trained worker is substantially higher compared to the wage premium, thus it seems plausible that to the extent that skills training provided by the firm are firm specific (due perhaps to their combination with firms' specific organizational routines), the appropriability concerns on these investments in training are mitigated.

In summary, there is a large and dynamic literature on intangible investments that shows sizable positive effects on productivity growth in frontier countries at the aggregate and micro levels (Haskel and Westlake, 2018, Tambe et al, 2020). Although in Latin America econometric studies are more limited and render mix results, case study-based evidence suggests that intangible based firms such as Mercado Libre, Globant, Despegar, OLX, Auth0, Rappi, dLocal, 99, Nubank, Prisma, GymPass, Softtek and Kio, among others, are able of competing with world leaders in their sectors, and, at the same time, coexist with a large number of firms that lag significantly behind in terms of productivity. However, in a context characterized by poor absorptive capacities, weak institutions, and poor technological infrastructure impacts of intangibles observed in developed countries both in terms of productivity and spillovers cannot be taken for granted. Hence there is need to get a deeper understanding on how the accumulation of intangible capital is affecting productivity at the firm level and if any sort of incomplete appropriability is affecting this impact.

3. Conceptual Framework

Intangible assets can increase productivity by improving product quality or reducing the average production costs of existing goods or simply by widening the spectrum of final goods or intermediate inputs available. So, in order to assess the productivity impacts of intangible assets our methodological starting point is an intangible capital augmented production function written as $Y_{it} = A_{it}F\left(L_{it}^{*}, M_{it}, K_{it}^{*}\right)$, where A_{it} is the technology that applies to the entire production function and Mit are intermediate inputs or materials. Here, total capital stock K_{it}^{*} is a combined variable that includes both tangible and intangible assets weighted by their relative productivities. While L_{it}^{*} is human capital augmented labor. Assuming a Cobb-Douglas production function and taking natural logs results in the standard (log) linear production function:

$$(1) \qquad y_{it} = \beta_0 + \beta_l l_{it}^{*} + \beta_m m_{it} + \beta_k k_{it}^{*} + \varepsilon_{it}$$

where lower-case letters refer to natural log and where:

(2) $$a_{it} = \beta_0 + \varepsilon_{it}$$

β_0 measures the mean efficiency level across firms and ε_{it} is the time and producer-specific deviation from that mean, which can then be further decomposed into observable (or at least predictable) and unobservable components. We follow Crepon, et al. (1998) to define a quality augmented total capital function as:

(3) $$K_{it}^{*} = \theta_T K_{T,it} + \theta_I K_{I,it}$$

Where the parameter θ_j captures the different qualities of intangible and tangible capital stocks respectively. Considering that total (non-quality adjusted) capital stock is simply $K_{it} = K_{T,it} + K_{I,it}$, we can use this identity into (3) to obtain $K_{it}^{*} = \theta_T (K_{it} - K_{I,it}) + \theta_I K_{I,it}$. We can rewrite this as $K_{it}^{*} = \theta_T K_{it}\left(1 - \frac{K_{I,it}}{K_{it}} + \frac{\theta_I}{\theta_T}\frac{K_{I,it}}{K_{it}}\right) = K_{it}\left[1 + \rho_I \frac{K_{I,it}}{K_{it}}\right]$ where $\rho_I = \left(\frac{\theta_I}{\theta_T} - 1\right)$ captures the relative productivity premium of intangible capital on tangible capital[5].

Assuming that this premium is relatively small and normalizing $\theta_T = 1$, we can take logs and use the approximation $k_{it}^{*} = k_{it} + \rho_I \frac{K_{I,it}}{K_{it}}$. Following a similar approach for human capital augmented labor we have $l_{it}^{*} = l_{it} + \rho_H \frac{H_{it}}{L_{it}}$ where H_{it} is the number of workers with a given level of human capital and ρ_H captures the relative productivity premium of human capital with regards to headcount labor. Substituting this together with (3) into (1) results in the following equation.

(4) $$y_{it} = \beta_l l_{it} + \beta_l \rho_H \left(\frac{H_{it}}{L_{it}}\right) + \beta_m m_{it} + \beta_k k_{it} + \beta_k \rho_I \left(\frac{K_{I,it}}{K_{it}}\right) + \omega_{it} + u_{it}\,.$$

and:

(5) $$\omega_{it} = \beta_0 + \vartheta_{it}$$

Where ϑ_{it} is the predictable component of ε_{it} and u_{it} is an i.i.d. component, representing unexpected deviations from the mean due to measurement error,

5 It measures how quality adjusted capital changes in percentage terms with changes in the intensity of intangible assets $\frac{dk^{*}}{d\left(\frac{KI}{K}\right)} = \rho_I$.

unexpected delays, or other external circumstances. In (4), the main parameter of interest is ρ_I which measures the capital productivity premium of intangibles with respect to tangible capital. The final impact of intangible capital on total output will be given by $\beta_k \rho_I$ which represents the percentage change in output in response to variations in the intangible intensity of total capital, which is also the impact of intangible intensity on total factor productivity. A nice feature of this specification is that it mitigates the collinearity problem between tangible and intangible capital stocks which, as the previous literature on R&D capital suggests, is a source of lack of precision and volatility in the results about R&D returns when using within estimates (Hall, et al. 2010). The key assumption underlying equation (4) is that intangible capital only affects capital productivity[6].

In order to explore the effects of intangible assets on wages, we need to recall from our previous discussion that if intangible assets are, at least partially, linked or stored into the firm's worker's brains, current employees will be imperfect substitutes with new hires, which generates a mechanism to extract rents from the firm in the form of a wage premium. Based on these considerations, innovative firms should share rents with its workers to increase the chances of retaining them (Kline, Petkova, Williams, and Zidar, 2018). The rent sharing mechanism depends on two considerations. First, how specific to the firm are the characteristics of ideas embedded in the intangible assets linked to their workers and second the degree of imperfect competition in the labor market. If ideas are generic, in other words if they can be applied without major adaptation or reverse engineering costs in firm's rivals, workers are expected to receive higher salary offers from competitors and so they will be in a better position to extract rents from the innovative firm. However, on the other hand, if ideas are firm specific, major adaptation or reverse engineering spending could be necessary to implement them in other firms. In this case, the salaries offered from the innovative firm's rivals are expected to be lower (as they should at least internalize adaptation or reverse engineering costs) and so innovative firm's employees will be in a worse position to extract rents from their current employer. In any scenario, innovative firms will be in a better position to retain the rents from their intangible investments whenever there are fewer or no rivals to them, in other words when there is imperfect

6 To the extent that much of intangible capital, in particular organizational capital, could be stored in key employees' talent, we cannot a priori rule out some effect of intangible capital on labor productivity (Crouzet, et.al. 2022). However, under this approach the problem is that we need to be able of separating the effects of intangible assets on total factor productivity among both labor and capital productivities leading to a problem of identification due to the lack of the necessary information in the dataset (for example, information on the number of R&D, design, and engineering workers).

competition in the labor market[7].

The theoretical discussion suggests a reduced-form model for wages of the form $W = W\left(\tilde{W}, S, \frac{K_I}{K}\right)$, where $\tilde{W}$ represents the external offers received by the employee that are independent from the characteristics of the ideas embedded into the intangible assets but that are affected by both employee level attributes (such as education and training) and firm level attributes (such as productivity, working environment, etc.). $\frac{K_I}{K}$ is the intangible assets intensity which effects on wages will depend on how generic the ideas embedded in the assets are. Finally, S captures the bargaining power of the firm relative to the employees which will also affect the effects of intangible assets on wages. So, we expect that the first derivative of the wage function with regards to $\tilde{W}$ and $\frac{K_I}{K}$ will be positive (and, in the last case, increasing with the outside value of intangibles assets related ideas) but that the cross derivative of W with regards to $\frac{K_I}{K}$ and S will be negative, because a higher S increases the bargaining power of the firm. So, following Van Reenen (1996), Konings and Vormelingen (2015) and Castillo et.al (2016), the reduced form model for the average wage at the firm level can be written as:

$$w_{it} = \delta_H \left(\frac{H_{it}}{L_{it}}\right) + \delta_I \left(\frac{K_{I,it}}{K_{it}}\right) + X_{it}\gamma + \varphi_{it} + \varepsilon_{it} \tag{6}$$

Where w_{it} is the average wage at the firm level (in log), X_{it} captures additional control variables including training, location and sector dummies determining average wages. Unobservables determinants of wages (such as labor quality among others) are represented by φ_{it}. Where in first instance we assume that firms are price takers in the labor market $(S = 0)$. The coefficients δ_H and δ_I capture the wage premiums of human capital and intangible assets intensities respectively. If firms are price takers in the labor market and ideas embedded into intangibles are generic, the capital productivity premium of intangible assets should be equivalent to the average wage premium $(\rho_I = \delta_I)$.

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7 Of course, although important, specificity of ideas and the degree of imperfect competition in the labor market are not the only factors affecting the sharing of innovation rents. Other determinants are related with firm's amenities such as geographic location or work environment, the duration of the relationship between the workers and the firm, involvement of workers in intangible assets intensive activities, hiring and separation costs, etc. Unfortunately, we lack enough detail information to control for these other factors which will be treated as unobservables in our study. However, we are confident that our identification strategy is robust enough as to control for their omission.

We discuss below how the results are affected if the firms are not price takers in the labor market.

4. Estimation Strategy

To have meaningful results for policy recommendations is critical to have unbiased estimates of intangible premiums for both equations. With regards to (4), unfortunately, OLS or fixed effects estimates do not provide a proper answer. Standard OLS techniques suffer from at least 2 problems. In first place, to the extent that (unobserved) productivity is partially anticipated by the firm, variable inputs hiring decisions will internalize productivity, so inputs will be endogenous and OLS estimates biased (Marschak and Andrews, 1944). Second, as firms enter and exit the panel, and given that firms make also exit decisions based on anticipated productivity shocks, exit won't be at random so, not taking the exit decisions into consideration, will lead to a problem of selection bias (Olley and Pakes, 1996).

To deal with these problems, we estimate the production function using different versions of the control function approach as suggested by Olley and Pakes (1996); Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015), among others. The three approaches explicitly model unobservable productivity as a function of some observable control variable highly correlated with the anticipated productivity shock, thus the anticipated productivity shock can be eliminated from the production function by inverting this function into observable variables. For example, if we follow Olley and Pakes (1996), investment decisions at the firm level can be shown to depend on capital and productivity $i_{it} = i_t\left(k_{it}, \left(\frac{K_{I,it}}{K_{it}}\right), \omega_{it}\right)$. Provided investment is strictly increasing in productivity, conditional on capital, this investment decision can be inverted allowing us to express unobserved productivity as a function of observables $\omega_{it} = h_t\left(k_{it}, \left(\frac{K_{I,it}}{K_{it}}\right), i_{it}\right)$, where $h_t(.) = i_t^{-1}(.)$. However, given that firms make also exit decisions based on anticipated productivity shocks, exit won't be at random so, not taking the exit decisions into consideration, will affect the consistency of the estimates (Olley and Pakes, 1996). Intuitively, the bias emerges because the firms' decisions on the allocation of inputs in a particular period are made conditional on its survival. If firms have some knowledge about their productivity ω_{it} prior to their exit, this will generate correlation between ω_{it} and the fixed input capital, conditional on being in the data set. This correlation has its origin in the fact that firms with a higher capital stock will (ceteris paribus) be more able to survive with lower ω_{it} relative to firms with a lower capital stock. This generates a negative correlation between the error and the capital stock $\left(E(k_{it}\omega_{it}\right) < 0)$ leading to a downward biased in the capital coefficient and to a further underestimation of returns rates of capital. To correct for this, we follow Olley and Pakes (1996) by including the survival probability into the control function (P_{it}) . Based on the discussion in this paragraph, equation (4) can be rewritten as:

$$y_{it} = \beta_l l_{it} + \beta_l \rho_H \left(\frac{H_{it}}{L_{it}} \right) + \beta_m m_{it} + \beta_k k_{it} + \pi_k \left(\frac{K_{I,it}}{K_{it}} \right) + h_t \left(k_{it}, \left(\frac{K_{I,it}}{K_{it}} \right), i_{it}, P_{it} \right) + u_{it} \tag{7}$$

Where $\pi_k = \beta_k \rho_I$. Equation (7) can be estimated by using a polynomial in capital stock, intangible assets share, investment, and survival probability. The method proceeds in two steps. In the first step, only the parameters of the free inputs are estimated (labor and materials) while the rest of the parameters are estimated in a second step assuming a Markov process for the productivity shocks. Levinsohn and Petrin (2003) argue that the Olley and Pakes (1996) method fails when investment cannot be inverted (for example, when firms report zero investment), and they propose using materials instead of investment in the proxy function for productivity. Ackerberg, Caves and Frazer (2015), instead, notice that when using materials none of the free inputs coefficients is identified in the first step, so they propose an adjustment to the methodology by which the parameters of all the inputs (free and predetermined) are identified in the second step.

Estimating the wage equation (6) suffers from the same problems as estimating the production function since human capital and intangibles intensity are likely to be correlated with unobservables. To correct for this, we follow Frazer (2001) and Konings and Vormelingen (2015) and use the productivity estimates from the productivity equation to control for the unobserved factors affecting wages. The assumption here is that the main component of the productivity shock after controlling for industry and year effects is unobserved labor quality. So, we estimate the following wage equation at the firm level:

$$w_{it} = \delta_H \left(\frac{H_{it}}{L_{it}} \right) + \delta_I \left(\frac{K_{I,it}}{K_{it}} \right) + X_{it}\gamma + \widehat{\omega_{it}} + \varepsilon_{it} \tag{8}$$

Where we assume that $\omega \approx \varphi$. Finally, in the specifications, all the regressions include year and industry dummies. Industry dummies are at ISIC two-digit level. Standard errors for all coefficients in both the production function and the wage equation are obtained using bootstrapping. After this we can derive the capital productivity premium of intangible assets from the estimated coefficient of intangible assets in (7). In other words:

$$\widehat{\rho_I} = \frac{\widehat{\pi_k}}{\widehat{\beta_k}} = \frac{\widehat{\beta_k \rho_I}}{\widehat{\beta_k}} \tag{9}$$

5. Data Description and Variables

Intangible investments are understood as a composite of three categories of assets: computerized information (software development, database development); innovative property (R&D, mineral exploration, copyright development, design, and other product development costs) and economic competences (market research & advertising, business process investment and training & skill development) (Corrado, Hulten and Sichel, 2005, 2009). In this paper, we use the National Enterprise Survey (ENE) of Peru which collects firm level information on firm's characteristics, infrastructure, human resources, management practices, information and communication technologies, financial products, production, sales, value added and assets.

The ENE produces an unbalance panel for 2015-2019. The total number of observations is 79,372. From this set, there are 43,821 firms observed for one year, 7,143 firms observed for two consecutive years, 2,818 firms tracked over three years, 1,779 firms followed over four years and 1,139 observed during the five years of the time setting. Overall, 12,879 firms are observed over two or more years. Unfortunately, the panel data structure strongly biases the sample composition towards large firms (7,883 of 12,879 firms). In terms of sectors, ENE is representative at two digits ISIC code (rev. 4). From this database, we obtain the main variables needed for the estimation of the production function such as total income, number of employees, fixed capital investments, and inputs (materials) expenditure and for the estimation of wage equation variables such as average wages, training provision and employees' education level[8].

The ENE survey also includes a module regarding fixed capital and intangible assets[9]. The production and asset section of the ENE survey has a specific question about the value of intangible assets which is defined as "*the representation of immaterial values, such as rights and privileges for the use of the firm with respect to its capacity to produce revenues and costs for goods and services that can generate future profits. For example, patents, concessions, trademarks, R&D expenditures, feasibility studies, among other*". The average ratio of intangible assets over total capital investments is 2.7% for the 2016-2019 period. In all the cases we use beginning of the period intangible capital stocks as the previous literature on R&D has found higher elasticities with end

8 All nominal variables are expressed in natural logarithm (ln) except ratios.

9 2015 ENE does not include this information, so the values for this year were imputed based on information from the following years at firm level.

of the period R&D due to simultaneity because of the feedback from output to current levels of intangible investments (Mairesse and Hall, 1994). We proceed in the same way with tangible capital stocks.

In order to adjust employment for labor quality we use the ratio of employees with tertiary education (undergraduate or graduate education) over the total number of employees[10]. To estimate the wage equation, we also include training provision as determinant of average wages. Training provision is a dummy variable that captures if an employee receives any training during the year of the survey. The average educational level for the 2015-2019 period is 30%.

Nominal variables were deflated by using different price indices deflators. We use the gross value-added deflator by ISIC code for total revenues, materials (inputs) are deflated using the wholesale price index, tangible capital was deflated using the gross private fixed capital formation price deflator and average wages are deflected by consumer price index. All deflator data is available at the National Institute of Statistics and Informatics of Peru (INEI).

Finally, we apply the blocked adaptive computationally efficient outlier nominator algorithm to identified multiple outliers in the 2015– 2019 ENE database. This technique uses the Mahalanobis distance from a basic subset of observations to separate outliers from non-outliers based on a specific threshold which is by default 0.15 percentile (Weber, 2010). We applied this technique to each ENE survey database. The final sample size to estimate the production and wage function is 27,654 observations.

Table 1 provides the descriptive statistics for the final working dataset. A Peruvian typical firm in the private sector employs on average 127 employees, generates around S/.26 million in output per year (equivalent to US$8 million) and has an average labor cost of around S/.3.9 million (equivalent to US$1.2 million). The largest average firm operates in the oil and gas and metal mining sectors, while the smallest ones are in the veterinary services and libraries and museums services.

The average fraction of intangible capital on total capital (or intangible capital intensity) is 2.7% being financial services, electricity, oil and gas, metal mining and insurance and pension funds the sectors with the largest intensities and traditional services such as residential care, accommodation, crop production and repair of domestic appliances those with the lowest (table 2). The proportion of firms that do not invest in intangibles is 63.2%. The intensity of intangibles of firms that do invest in intangibles is 7.3%, which implies that the main reason for the low share of intangibles in total capital stock in the total sample is that few firms actually do invest in intangibles.

10 2019 ENE does not include data on employees' education level. For 2019, this variable is calculated as 2015-2018 average.

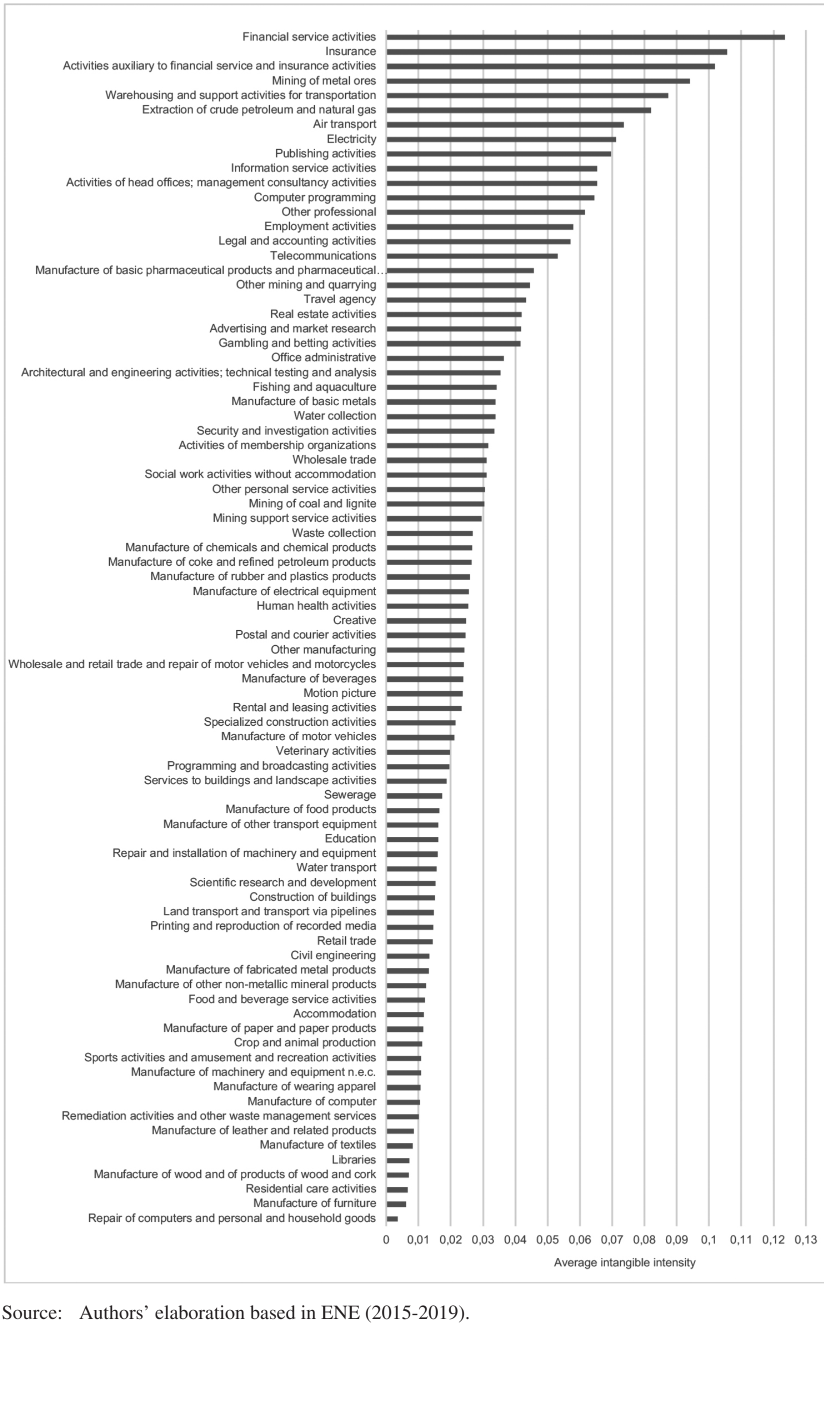
TABLE 1
SUMMARY STATISTICS

VARIABLES	Mean	Std. Dev.	10th Perc.	50th Perc.	90th Perc.	N
Employees	127	472	3	15	264	27,654
Labor cost (S/)	3,964,000	18,270,000	10,200	207,334	8,494,000	27,654
Labor cost (USD)	1,204,863	5,553,191	3,100	63,019	2,581,763	27,654
Labor cost per employee (S/)	30,759	193,050	2,400	13,127	55,777	27,654
Labor cost per employee (USD)	9,349	58,678	729	3,990	16,953	27,654
Education	0.299	0.276	0	0.296	0.750	27,654
Output (S/)	26,600,000	108,900,000	53,190	1,514,000	58,040,000	27,654
Output (USD)	8,085,106	33,100,304	16,167	460,182	17,641,337	27,654
Value added (S/)	22,040,000	98,330,000	0	664,260	47,330,000	27,654
Value added (USD)	6,699,088	29,887,538	0	201,903	14,386,018	27,654
Ratio labor cost over output	0.149	0.168	0.137	0.146	0.192	27,654
Intangible assets over total capital (for total number of firms)	0.027	0.100	0	0	0.038	27,654
Intangible assets over total capital (only firms that invest in intangibles)	0.073	0.154	0.002	0.030	0.184	10,179

Source: ENE (2015-2019).

TABLE 2

INTANGIBLE INTENSITY BY SECTOR (CIIU REV. 4)



Source: Authors' elaboration based in ENE (2015-2019).

6. Econometric Results

In the empirical estimates our main dependent variable is value added (output minus materials). There are several reasons to prefer value added over sales when using firm level data. *First*, the materials-output ratio can vary greatly across firms because different degrees of vertical integration; *second*, proper modelling of the demand for intermediate inputs would probably require modelling adjustment costs related to the stock of materials; and *third*, data on materials are prone to measurement errors when using accounting data (Hall et al., 2010). We do not impose constant returns to scale in the production function because the previous empirical literature on R&D suggests that doing this tends to overestimate the returns to R&D (Hall and Mairesse, 1995). So, using value added deflated data, we first estimate the impact of intangible assets on the productivity (equation 4) and on average wages (equation 6). For the estimation of equation (6) we included as control variable the total factor productivity (TFP) estimated from equation (4) among other control variables which are determinants of wages such as firm provided training and education level of labor force. Our estimation strategy includes the results obtained by applying the control function approach-based methodologies suggested by Olley and Pakes (1996); Levinsohn and Petrin (2003), and Ackerberg, Caves and Frazer (2015) always including the selection bias correction. The results from Table 3 suggest that the control function corrections work in the expected direction as the coefficient of labor decreases with respect to the OLS benchmark (for the OP and LP methods) and the coefficient of capital increases (for the OP and ACF specifications). Using as benchmark the ACF results, labor elasticity (0.72) and capital elasticity (0.34) are within expected values based on the inherited literature on production function estimates. Also, the findings suggest that there are constant returns to scale. The coefficient that captures the impact of intangibles intensity is very similar across the different control function results (with the only exception of the fixed effects results that are rather poorly estimated). Given that this coefficient captures the contribution of intangibles to total factor productivity, by focusing on the ACF result, we can infer that one standard deviation increase in intangible assets intensity (0.10) produces an increase of 6.8% in total factor productivity. Using the estimated results for input elasticities together with equation (9) we calculate that the productivity premium of intangibles on tangible capital is 1.93 (based on the ACF results). In other words, the productivity premium of intangible assets is almost two times the marginal productivity of tangible investments. Additional results suggest that education has also a strong premium on the productivity of labor with a coefficient of 0.57. Such large productivity premium is consistent with the findings by Benavente et.al. (2006) for R&D returns in Chile which

TABLE 3

IMPACT OF INTANGIBLES ON PRODUCTIVITY AND WAGES

(BASELINE MODEL – VALUE ADDED)

VARIABLES	**OLS**	**FE**	**OP**	**LP**	**ACF**
			PRODUCTION FUNCTION		
LABOR (β_l)	0.704***	0.414***	0.573***	0.613***	0.727***
	(0.0096)	(0.0385)	(0.0059)	(0.0024)	(0.0348)
Education ($\beta_l \rho_H$)	0.805***	-0.0960	0.423***	0.558***	0.591***
	(0.0394)	(0.0990)	(0.0047)	(0.0565)	(0.0273)
Capital (β_k)	0.268***	0.179***	0.362***	0.262***	0.345***
	(0.0050)	(0.0224)	(0.0375)	(0.0327)	(0.0063)
Intangibles ($\beta_k \rho_I$)	0.658***	0.411*	0.833***	0.706***	0.683***
	(0.0950)	(0.2450)	(0.0355)	(0.1490)	(0.0148)
WAGE EQUATION					
INTANGIBLES (δ_I)	0.804***	0.299*	0.681***	0.834***	0.832***
	(0.0725)	(0.1680)	(0.0704)	(0.0684)	(0.0687)
TFP (ω_{it})			0.321***	0.308***	0.303***
			(0.0059)	(0.0049)	(0.0050)
TRAINING (γ)	0.395***	0.00770	0.288***	0.346***	0.350***
	(0.0155)	(0.0347)	(0.0147)	(0.0147)	(0.0148)
EDUCATION (δ_H)	0.598***	-0.0829	0.453***	0.564***	0.570***
	(0.0290)	(0.0651)	(0.0284)	(0.0277)	(0.0278)
OBSERVATIONS	23,480	7,348	21,595	26,884	26,884
SECTOR	YES	YES	YES	YES	YES
REGION	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models correct for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise), two digits sector dummies and time effects. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy), two-digit sector dummies and time effects. Where OLS = Ordinary Least Squares, FE= Fixed Effects, OP = Olley and Pakes, LP = Levinsohn and Petrin and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

finds that in a balanced sample of firms the rates return to R&D are almost 3 times larger than in the case of fixed capital (0.54 vs. 0.18)[11].

When examining the wage equation, we obtain that the intangible assets intensity shows a coefficient of 0.83 on the (ln) wages at the firm level. Firms that provide training also pay higher average wages (35%), while more productive firms also pay higher average wages with an elasticity of 0.30 (in other words, about one third of a total productivity increase at the firm level translates to average wages). The large gap we found between capital productivity and wage premiums suggest that only 43% of the productivity premium goes to workers' wages. Although this figure is relevant and it could suggest some policy intervention to compensate firms, still the majority of the returns from intangibles are appropriated by the firms. Although lower than in the case for intangibles, we also found a large wage premium for human capital (0.59). Table 3 suggest that the productivity premium of human capital is 0.80 (0.59/0.73), which indicates that about 60% of the productivity premium of human capital is shared by the firm with its workers.

To check the extent that our results are robust to different definitions of the dependent variable, we also estimated the basic model using total output as the main dependent variable due to the concern that measuring errors in material could also affect value added measurements. In fact, when using value-added if materials are poorly measured (considering that value added is the difference between total output and materials) this could affect the precision of the results. So, instead of using value-added, we also estimate our baseline model using output as dependent variable. The results are summarized in Table 4.

If we take as reference the ACF results, we obtain production function coefficients which are very similar to the ones when using value-added. Indeed, labor elasticity (0.70) and capital elasticity (0.30) are within the expected based on the inherited literature on production function estimates. Also, the findings suggest that there are constant returns to scale. When analyzing the effects of intangible capital on total factor productivity, Table 4 suggests a little higher total effect (0.72 vs 0.68). The main message is similar as before, intangibles are a driving force underlying total factor productivity growth. With regards to the wage equation the results are similar to the ones in Table 3. Indeed, the estimated wage premium of intangibles is 0.88 with important wage effects of productivity, training, and education.

However, the results in Table 4 suggest some changes in the estimated productivity premium of intangible capital. Indeed, a slightly higher coefficient of intangibles intensity combined with relatively lower output elasticities of capital (0.30 vs 0.34) leads to an increase in the computed productivity pre-

11 In the unbalanced sample the productivity premium is lower (1.79)

mium of intangibles on the productivity of capital (2.40 vs 1.93)[12]. In other words, although the results seem to be robust to the main parameters of both the production function and the wage equation, given the high nonlinearity of the parameters of equation (9), small changes in the estimated parameters increases the estimated premium of intangible assets on the productivity of capital. However, we believe, the main conclusions of the previous results are not altered. Intangible capital is a powerful driving force for total factor productivity growth at the firm level and about 64% of the capital productivity premium is appropriated by the firm. Despite this, still 36% is shared with the workers.

Summing up, if intangibles are embedded in labor, this creates concerns at the firm level to the extent that investors can appropriate the results of their investments in intangible capital, and if this knowledge is general, to the extent that it can be used in other firms (labor mobility could also benefit rival firms). Perhaps this is the main reason why, despite the potentially huge impact of intangibles on total factor productivity, very few firms carry out significant investments in it (with many firms with zero intangibles investment overall).

12 Based on the ACF results and using equation 9.

TABLE 4
IMPACT OF INTANGIBLES ON PRODUCTIVITY AND WAGES (BASELINE MODEL - OUTPUT

VARIABLES	OLS	FE	OP	LP	ACF
PRODUCTION FUNCTION					
LABOR (β_l)	0.688***	-0.00454	0.573***	0.613***	0.701***
	(0.0088)	(0.0471)	(0.0059)	(0.0024)	(0.0250)
Education ($\beta_l \rho_H$)	0.740***	0.836***	0.423***	0.558***	0.592***
	(0.0354)	(0.1170)	(0.0047)	(0.0565)	(0.0046)
Capital (β_k)	0.264***	-0.122***	0.362***	0.272***	0.308***
	(0.0046)	(0.0257)	(0.0375)	(0.0338)	(0.0099)
Intangibles ($\beta_k \rho_I$)	0.660***	-0.668**	0.833***	0.729***	0.720***
	(0.0872)	(0.3020)	(0.0355)	(0.0052)	(0.0170)
WAGE EQUATION					
INTANGIBLES (δ_I)	0.848***	0.288*	0.704***	0.882***	0.880***
	(0.0731)	(0.1660)	(0.0690)	(0.0676)	(0.0679)
TFP (ω_{it})			0.445***	0.456***	0.453***
			(0.0066)	(0.0064)	(0.0065)
Training (γ)	0.399***	-0.008	0.278***	0.330***	0.334***
	(0.0155)	(0.0341)	(0.0143)	(0.0145)	(0.0146)
Education (δ_H)	0.606***	-0.020	0.445***	0.550***	0.559***
	(0.0293)	(0.0640)	(0.0279)	(0.0274)	(0.0275)
OBSERVATIONS	27,654	9,429	21,595	26,884	26,884
SECTOR	YES	YES	YES	YES	YES
REGION	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models correct for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise), two digits sector dummies and time effects. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy), two-digit sector dummies and time effects. Where OLS = Ordinary Least Squares, FE= Fixed Effects, OP = Olley and Pakes, LP = Levinsohn and Petrin and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

7. Model Extensions

In this section, we introduce several additional experiments because the results presented in section 6 could be affected by several factors. *First*, the effects could depend on the actual composition of the vector of intangible assets. Not all intangibles are expected to suffer from partial appropriability in the similar extent, so controlling for this is important in order to correct more precisely for market failures. *Second*, real firms most of the time are also multiproduct firms. This implies that the production function should be estimated at the product line level which is impossible due to lack of information on the allocation of inputs (and intangible assets) across the different product lines. Moreover, in the case of intangible assets this is important because intangibles are also non-rival in use within firms, which means that the same intangible could be use at the same time across the different product lines. Therefore, it is expected that the productivity premium of intangibles will be higher in multiproduct firms compare to single product firms. *Third*, the baseline results could also be affected by the influence of imperfect competition. If there is imperfect competition in the product markets, the estimated elasticities are a mixed between the factor shares and the mark-up. Although exploring the extent to which firms deviate from perfect competition might be interesting, we show that this problem is not relevant to untangling the relative premiums of intangible assets on capital productivity (to the extent that the mark-up parameter factors into the production function). More important, however, is to explore whether the results in the wage equation could be affected by distortions in the labor markets. In particular if there is monopsonic competition in the labor markets, mark-downs could affect the estimated wage premium of intangibles. In this section, we assess the extent to which our results are affected by these problems.

7.1 R&D vs Other Intangible Assets

The main model in section 6 estimates the capital productivity premium of intangible assets as a whole, without differentiating between types of intangibles as this information is not available in the ENE survey. Unfortunately, ENE lacks enough detail as to identify the sample of firms that do R&D. So, to examine the impact of intangible assets on productivity and wages depending on its type, we grouped companies in high and low R&D intensity sectors. For this split, we follow the OECD's taxonomy of economic activities based on R&D intensity developed by Galindo-Rueda and Verger (2016) in which R&D intensity is defined as the ratio of R&D to value added within an industry and economic activities are clustered into 5 groups: high, medium-high, medium,

medium-low, and low R&D intensity industries. Considering the limited sophistication of the Peruvian economy and its low levels of R&D investment, we include medium, medium-high, and high intensity industries in the high R&D intensity sectors group while low and medium-low R&D intensity industries are included under the low R&D intensity sectors group.

Table 5 summarizes the main results of this exercise. Following this classification, we found that the impact of intangibles on total factor productivity is much higher in the case of R&D intensive sectors (0.72 vs 0.61). The intangible assets capital productivity premium is also slightly higher in R&D intensive sectors (2.28 vs 1.79)[13]. In both subsamples we do not observe major departures from constant return to scales, which is reassuring of our previous findings. With regards to the wage premium, we also found that intangible assets impact is slightly higher in the case of R&D intensive sectors (0.84 vs 0.81). Based on these results the share of the capital productivity premium which is captured by labor is 36% in high R&D intensive sectors and 45% in the low R&D intensive sectors. If we interpret this as a signal of a market failure, it seems that the share of the capital productivity premium that goes to labor is more important in low R&D intensive sectors (perhaps this is the main reason of the low R&D intensity in these sectors).

[13] Based on the ACF results and using equation 9.

TABLE 5

IMPACT OF INTANGIBLES ON FIRMS FROM HIGH AND LOW R&D INTENSITY SECTORS

VARIABLES	High R&D intensity sectors (High R&D=1)			Low R&D intensity sectors (Low R&D=0)		
	OLS	**OP**	**ACF**	**OLS**	**OP**	**ACF**
PRODUCTION FUNCTION (VALUE ADDED)						
LABOR (β_l)	0.757***	0.641***	0.785***	0.692***	0.565***	0.725***
	(0.0422)	(0.0148)	(0.218)	(0.0102)	(0.0134)	(0.0064)
EDUCATION ($\beta_l \rho_H$)	0.771***	0.281	0.337***	0.828***	0.462***	0.643***
	(0.1620)	(0.2150)	(0.0194)	(0.0426)	(0.0373)	(0.0112)
CAPITAL (β_k)	0.268***	0.729*	0.320**	0.270***	0.366***	0.342***
	(0.0220)	(0.400)	(0.135)	(0.0053)	(0.0212)	(0.0138)
Intangibles ($\beta_k \rho_I$)	0.914***	2.619***	0.728***	0.604***	0.805***	0.615***
	(0.3330)	(0.6910)	(0.0586)	(0.1010)	(0.0335)	(0.0076)
WAGE EQUATION						
INTANGIBLES (δ_I)	0.841***	0.463*	0.845***	0.787***	0.689***	0.815***
	(0.2740)	(0.2660)	(0.2600)	(0.0768)	(0.0746)	(0.0726)
TFP (ω_{it})		0.412***	0.371***		0.318***	0.303***
		(0.0294)	(0.0223)		(0.0061)	(0.0052)
TRAINING (γ)	0.366***	0.188***	0.335***	0.405***	0.297***	0.357***
	(0.0651)	(0.0681)	(0.0618)	(0.0164)	(0.0154)	(0.0156)
EDUCATION (δ_H)	0.936***	0.726***	0.898***	0.605***	0.469***	0.585***
	(0.1290)	(0.1380)	(0.1230)	(0.0310)	(0.0303)	(0.0297)
OBSERVATIONS	1,520	1,116	1,696	20,740	19,560	23,953
SECTOR	YES	YES	YES	YES	YES	YES
REGION	YES	YES	YES	YES	YES	YES
YEAR	YES	YES	YES	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models correct for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise) and two digits sector dummies. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy) and two-digit sector dummies. Where OLS = Ordinary Least Squares, OP = Olley and Pakes, and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

7.2 Scope Economies and Multiproduct Firms

In the basic model, we do not consider the product mix of the firm. If firms produce multiple products, potentially differing in their production technology; failure to estimate the production function at the appropriate product level, rather than at the firm level, will introduce biased input elasticities and productivity premiums (Bernard, Redding and Schott (2005)). In the case of intangibles assets, considering that the firm can have multiple product lines is important due to the non-rival nature of intangible assets (Corrado, et.al. 2022 and Bronnenberg, et.al. 2022). For example, a company can deploy a marketing campaign that affects the demand of the whole mix of products fabricated by the firm. In the same extent, process innovation, such as the adoption of just-in-time, could increase the efficiency of the different production lines of a car manufacturer. So, if non rivalry is important, we should expect a higher productivity effect of intangibles in multiproduct vs single product firms. Fortunately, in the survey we can differentiate between firms producing single or multiple products, so we can split the sample of firms between these two groups. The results of this exercise are presented in Table 6.

Table 6 summarizes the main results of this exercise. Following this classification, we found that the impact of intangibles on total factor productivity is slightly higher in the case of multiproduct firms (0.65 vs 0.60). The intangible assets capital productivity premium, however, is higher in single product firms (2.77 vs 2.32). With regards to the wage premium, we do not find differences between both subsamples (0.82 vs 0.83). Based on these results the share of the capital productivity premium which is captured by labor is 35% in multiproduct firms and 30% in single product firms. If we interpret this as a signal of a market failure, it seems that is more important in multiproduct firms (perhaps the new product designs are more easily transferred and imitated by other firms), however the overall results differences between both samples are rather small.

TABLE 6

IMPACT OF INTANGIBLES ON MULTI-PRODUCT AND SINGLE-PRODUCT FIRMS

VARIABLES	Multi-product firms (Multiproduct=1)			Single-product firms (Multiproduct=0)		
	OLS	**OP**	**ACF**	**OLS**	**OP**	**ACF**
Production function (value added)						
Labor (β_l)	0.691***	0.499***	0.689***	0.761***	0.558***	0.733***
	(0.0170)	(0.0087)	(0.0078)	(0.0195)	(0.0140)	(0.0225)
Education ($\beta_l \rho_H$)	0.713***	0.112	0.584***	0.652***	0.121***	0.428***
	(0.0760)	(0.0704)	(0.0042)	(0.0769)	(0.0398)	(0.0108)
Capital (β_k)	0.285***	0.240**	0.283***	0.234***	0.265***	0.216***
	(0.0086)	(0.1200)	(0.0147)	(0.0098)	(0.0622)	(0.0365)
Intangibles ($\beta_k \rho_I$)	0.569***	0.752*	0.652***	0.644***	0.613*	0.604***
	(0.1610)	(0.4070)	(0.0090)	(0.1850)	(0.3660)	(0.0078)
Wage equation						
Intangibles (δ_I)	0.771***	0.700***	0.825***	0.810***	0.513***	0.838***
	(0.123)	(0.122)	(0.116)	(0.138)	(0.136)	(0.1300)
TFP (ω_{it})		0.364***	0.309***		0.311***	0.287***
		(0.0103)	(0.0081)		(0.0111)	(0.0091)
Training (γ)	0.513***	0.309***	0.445***	0.365***	0.236***	0.311***
	(0.0270)	(0.0245)	(0.0255)	(0.0317)	(0.0283)	(0.0299)
Education (δ_H)	0.617***	0.169***	0.594***	0.326***	0.123**	0.302***
	(0.0542)	(0.0532)	(0.0509)	(0.0577)	(0.0542)	(0.0545)
Observations	10,696	8,389	10,662	8,153	6,641	8,127
Sector	YES	YES	YES	YES	YES	YES
Region	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models control for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise) and two digits sector dummies. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy) and two-digit sector dummies. Where OLS = Ordinary Least Squares, OP = Olley and Pakes, and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

7.3 Imperfect Competition

Imperfect competition can operate in both product and input markets. We first focus on the influence of imperfect competition in product markets. Following Klette (1996) if we assume a model of profit maximizing producer behavior, imperfect competition in output market and perfect competition in input markets, the marginal revenue product of an input will be equal to its marginal cost. So, as noted by Hall (1988) and others, it follows that:

$$\beta_h = \mu\theta_h = \frac{\sigma}{1+\sigma}\theta_h \tag{10}$$

Where θ_h is the cost share of factor h as a share of revenues and μ is the mark-up given as $\frac{\sigma}{1+\sigma}$. Where σ is the elasticity of substitution (demand) between differentiated goods in the industry $(-\infty < \sigma < -1)$. A nice feature of (10) is that deviations from product perfect competition can be assessed by simply ratio between the estimated elasticity and the factor cost share, which normally is an observed variable in industrial surveys. However, we claim that deviations from product perfect competition do not affect the relative premium of intangible assets on capital productivity, which can be deducted immediately from the way this premium is obtained in equation (9):

$$\rho_I = \frac{\pi_k}{\beta_k} = \frac{\beta_k \rho_I}{\beta_k} = \frac{\frac{\sigma}{1+\sigma}\theta_k \rho_I}{\frac{\sigma}{1+\sigma}\theta_k} = \frac{\theta_k \rho_I}{\theta_k} \tag{11}$$

In other words, the mark-up parameter (μ) scales-up input elasticities both in the numerator and denominator of equation (11). So, the intangible premium could be estimated by using the capital cost shares (θ_h) that in principle could be computed from the data. The situation becomes more complex if there is imperfect competition in the labor market.

If there is imperfect competition in the labor market firms could pass less of the increase in capital productivity due to intangible assets investments to their workers' wages. If this is the case, the intangible assets wage premium (δ_I) in (9) will be a mix of how generic the ideas embedded in human capital are and the mark down due to imperfect competition. So, estimating the mark down in the labor market due to imperfect competition is important in order to property compute the share of intangible assets effects on capital productivity that goes to labor. The issue is how to obtain a reliable estimate of this mark down at the firm level. Our approach rests on the idea of estimating monopsony market power at the labor market level (Bunting, 1962). This approach uses a simple location-based measure of market power as follows. We construct an overall measure of the percentage of the industry-specific labor market that each firm employs (which is the number of workers at firm i divided the number of workers in firm i's region and in firm i's industry or sh_{ijt}). While this variable is far from a perfect measure of an employer's power to set wages, it has the advantage that is a measure that can be constructed transparently from the data and that endogeneity problems are of a less concern. After constructing this variable, we added it as an additional control in equation (6) where we also interact this variable with both human capital and intangible assets intensities. If the interaction terms are negative, we can claim that there is imperfect competition in the labor market and firms are using it to reduce the effect of intangible assets on wages (in other words firms are using market mechanisms to appropriate the effects of intangible assets on productivity).

Table 7 summarizes the results. We found that the wage premiums of intangible assets and human capital are negatively affected by market power in the labor markets (although the results are significant only in the case of human capital). However, if we take as valid the results in the last column of the table (ACF), we obtain that the wage premium of intangible assets in the case of monopsony is much lower than in the case of perfect competition in the labor market (0.35 vs 0.85). The difference in the wage premium between monopsony and perfect competition is also observed in the case of human capital (0.17 vs 0.59). The results suggest that wage compression due to imperfect competition is a channel through which firms could increase their control of innovation rents.

TABLE 7

IMPACT OF IMPERFECT COMPETITION IN THE LABOR MARKET

VARIABLES	OLS	OP	ACF
Intangibles (δ_I)	0.851***	0.695***	0.854***
	(0.0760)	(0.0738)	(0.0721)
Market power*Intangibles ($sh_{ijt}*\delta_I$)	-1.032**	-0.329	-0.500
	(0.446)	(0.449)	(0.420)
Education (δ_H)	0.630***	0.471***	0.591***
	(0.0304)	(0.0298)	(0.0292)
Market power*Education ($sh_{ijt}*\delta_H$)	-0.674***	-0.369**	-0.412**
	(0.179)	(0.171)	(0.171)
Market power (sh_{ijt})	0.150**	-0.0329	0.135*
	(0.0759)	(0.0717)	(0.0722)
TFP (ω_{it})		0.321***	0.303***
		(0.00587)	(0.0049)
Training (γ)	0.397***	0.291***	0.350***
	(0.0155)	(0.0147)	(0.0148)
Observations	23,480	21,595	26,884
Sector	YES	YES	YES
Region	YES	YES	YES
Year	YES	YES	YES

Source: *P<0.10; ** P<0.05; *** P<0.01. Standard errors in parentheses. All control function models correct for attrition of firms. To estimate the production function regressions, we include as control variables: years of establishment functioning, a dummy variable for the location of the firm (1 if Lima, 0 otherwise) and two digits sector dummies. The estimation of the wage equation includes training and educational level as determinants of average wages and control variables such as TFP, location (dummy) and two-digit sector dummies. Where OLS = Ordinary Least Squares, OP = Olley and Pakes, and ACF = Ackerberg, Caves and Frazer method. For the corrections that control for attrition of firms we follow Rovigatti and Mollisi (2018).

8. Policy Implications

Estimating the effect of intangible capital investment on average wages is important to understand the extent to which the returns of these investments are appropriated either by the firm or by the workers. To the extent that the contribution of intangible investments to capital productivity is higher than the effect of intangible investments on average wages we can assume (partial) appropriability of these investments by the firms. This can help us investigating whether there are some market failures (in terms of externalities) that can merit public policy intervention. Several possibilities can be explored.

If there is perfect competition in the labor and $\rho_I > 0$ and δ_I =0 we can assume that the firm appropriates all the returns market from intangible investments or equivalent that intangible related knowledge is firm specific, so there is no room for policy intervention. On the other hand, if $\rho_I = \delta_I > 0$ it implies that all the returns on intangibles are internalized in wages and so that intangible related knowledge is generic. To the extent that workers can leave the company and move to other competitors of the firm there will be a market failure that will require government subsidizing the accumulation of intangible investments. Finally, if $\rho_I > \delta_I > 0$ we have a problem of partial appropriation by the firm, and some degree of policy intervention might be needed.

In this context $\frac{\delta_I}{\rho_I}$ could be considered as proxy of the subsidies to be provided to compensate the firm for the lack of appropriability of its investments in intangibles. In other words, public policies should be subsidizing the share of innovation rents that goes to workers only. Our findings of the baseline model for value added in Table 3 suggest that there is partial appropriability of intangible investments in Peru by contrasting the effects of intangibles on wages with the effects on capital productivity. This result holds for most of extension models which indicates that the conclusions drawn are robust. Therefore, our findings suggest that policy interventions might be needed to compensate firms for spillover effect of intangible assets in Peru.

TABLE 8

SUMMARY RESULTS AND POLICY RECOMMENDATIONS

Intangible Assets	ρ_I	δ_I	$\frac{\delta_I}{\rho_I}$
Perfect competition in the labor market		0.854	43.4%
Average competition in the labor market	1.97	0.604	30.7%
Monopsony in the labor market		0.354	18.0%
Human Capital	ρ_H	δ_H	$\frac{\delta_H}{\rho_H}$
Perfect competition in the labor market		0.591	51.8%
Average competition in the labor market	1.14	0.385	33.8%
Monopsony in the labor market		0.179	15.7%

The results in Table 8 suggest that in a scenario of perfect competition in the labor market, about 43% of the capital productivity premium of intangible assets is shared with the workers (52% in the case of human capital). This implies that the ideas associated with intangible assets are in great part firm specific. In the case of monopsony in the labor market the proportion of the capital productivity premium that is shared with the workers declines to just 18% (15% in human capital). This implies that wage compression due to monopsony is a major source of intangible assets appropriability (and also of education investments). So, at the moment of deciding whether intangible investments should be subsidized by public policies is critical to have some idea of the degree of imperfect competition in the labor market. A flat subsidy rate across firms from different sectors could imply a waste of limited fiscal resources because it would be too low for firms operating in labor markets close to perfect competition and it will be too high for firms with high monopsonic power.

9. Conclusions

The global economy is entering the age of intangibles, in which intangible capital investment, including R&D and other expenditures, has risen dramatically compared to the tangible capital one and has become a major source of productivity growth in developed economies. However, there is not much evidence in emerging economies mostly due to the lack of information. This paper closes this knowledge gap by using a large firm-level panel data set with information on intangibles from Peru for the period 2015-2019. With a per capita GDP of US$13.000, Peru is a middle-income country in the LAC region, so its findings can be somehow considered as representative of the whole region. We use a control function approach to estimate production functions and wage equations at the firm level to infer the capital productivity and wage premiums of intangible assets.

Our results indicate that the capital productivity premium associated with the intensity of intangible assets at the firm level is larger than the wage increase. More precisely, the results suggest that the capital productivity of intangibles is around twice the productivity of tangible assets, which is in line with the previous research by Benavente et.al. (2006) on both the returns to R&D and to fixed capital investment. Moreover, intangible assets accumulation is a major determinant of total factor productivity as an increase of one standard deviation in the intensity of intangible assets (0.10) leads to a 7% higher total factor productivity at the firm level. Moving to labor market related results, our research points out that there is a wage premium associated with intangible assets which suggests that firms are sharing the rents of their innovations with their workers, which creates appropriability concerns leading to a potential need for policy intervention. Our research also extends the basic model to examine how different factors such as the type of intangible assets, multi-product mix and imperfect competition in the labor market have an impact on the results. After separating the sample in different groups according to these factors (firms that pertain to R&D intensive sectors vs firms that do not or multi-product firms vs single-product firms) the findings remain consistent, suggesting that the conclusions drawn are robust. For instance, total factor productivity impacts of intangibles are higher for firms in R&D intensive sectors and multiproduct product firms. We also found that intangibles rent sharing depends on the degree of monopsonistic power of the firm in the labor market. Firms that enjoy labor market power are able to retain a significatively larger fraction of intangibles rents. This has important policy implications for innovation policy design. For example, when making intangible assets investment decisions firms might not be able to appropriate the full rents of their investments which opens the possibilities for the government to implement intangible subsidies, however the subsidy rate should decline with the degree of monopsonistic power of the firm. This is important as most of the support to innovation in Peru (and other countries in the region) does not internalize in the policy designs the importance of market power leading to flat subsidy rates across firms and sectors, potentially leading to subsidy rates that are lower than it is needed by firms that operate in an environment close to perfect competition in the labor market and otherwise higher than it is needed by firms that enjoy monopsonistic power.

Although our results shed lights on the impact of intangibles on productivity and wages for a Latin America country such as Peru, there are potential limitations in our study particularly with the composition of the ENE survey which may affect the results. First, the ENE survey sample is heavily biased towards large firms considering that in Peru these companies only account for no more than 3% of the total number of firms in the economy. Second, there are only around a thousand firms for all five years of the survey which limited our capacity of analyzing the effects of intangibles over time. Third, and final, there is not a consistent definition to measure R&D investment among all the different survey periods, which does not allow us properly analyzing the potentially different effects of R&D in comparison with other intangibles. Improving upon these shortcomings is part of the future research agenda.

References

Aboal, D. and E. Tacsir. (2018). "Innovation and productivity in services and manufacturing: the role of ICT", Industrial and Corporate Change, Vol. 27; 221-241.

Ackerberg, D. A., K. Caves, and G. Frazer. (2015). "Identification properties of recent production function estimators". Econometrica, Vol. 83; 2411–2451.

Baldwin, J. R. and D. Sabourin. (2002). "Impact of the Adoption of Advanced Information and Communication Technologies on Firm Performance in the Canadian Manufacturing Sector", OECD Science, Technology and Industry Working Papers 2002/1.

Bartel, A. P. (1995). "Training, Wage Growth, and Job Performance: Evidence from a Company Database," Journal of Labor Economics Vol. 13; 401–425.

Benavente J. M., J. De Gregorio and M. Nuñez. (2005). "Rates of Return for Industrial R&D in Chile", University of Chile, Working Papers 220.

Bernard, A. B., S. Redding, and P. K. Schott. (2005). “Products and Productivity”. NBER Working Paper 11575.

Black, S. E., and L. M. Lynch. (2001). “How to Compete: The Impact of Workplace Practices and Information Technology on Productivity”, The Review of Economics and Statistics, Vol. 83(3); 434–445.

Bloom, N., M. Schankerman, and J. Van Reenen. (2007). “Identifying Technology Spillovers and Product Market Rivalry”, NBER Working Paper 13060.

Bloom, N., R. Sadun, and J. Van Reenen. (2012). “Americans Do IT Better: US Multinationals and the Productivity Miracle.” American Economic Review, Vol. 102(1); 167–201.

Bresnahan, T.; E. Brynjolfsson and L. Hitt. (2002). “Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence”, Quarterly Journal of Economics, Vol.117(1); 339-376.

Bronnenberg, Bart J., J.P. Dubé, and C. Syverson. (2022). “Marketing Investment and Intangible Brand Capital”, Journal of Economic Perspectives, Vol. 36(3); 53-74.

Bunting, R. L. (1962). Employer Concentration in Local Labor Markets. Chapel Hill: University of North Carolina Press.

Castillo, V., L. Figal Garone, A. Maffioli, S. Rojo, and R. Stucchi. (2019). “Knowledge Spillovers through Labour Mobility: An Employer–Employee Analysis”, The Journal of Development Studies, Vol. 3; 469-488.

Cereda, M., G. Crespi, C. Criscuolo and J. Haskel. (2005). Design and company performance: evidence from the Community Innovation Survey. DTI Report.

Choi, J. N. Goldschlag, J. Haltiwagner and D. Kim. (2023). “Early Joiners and Startup Performance”, NBER Working Paper 28417.

Coe, D. T. and E. Helpman. (1995). “International R&D spillovers,” European Economic Review, Vol. 39(5); 859-887.

Corrado, C., C. R. Hulten and D. Sichel. (2005). “Measuring Capital and Technology: An Expanded Framework,” in C. Corrado, J. Haltiwagner, and D. Sichel (eds.), Measuring Capital in the New Economy, Studies in Income and Wealth, Vol. 66; 11–46. Chicago: University of Chicago Press.

Corrado, C., C. R. Hulten and D. Sichel. (2009). “Intangible Capital and U.S. Economic Growth,” Review of Income and Wealth Vol. 55(3); 661–685.

Corrado, C., J. Haskel, C. Jona-Lasinio, and M. Iommi. (2022). “Intangible Capital and Modern Economies“, Journal of Economic Perspectives, Vol. 36(3); 3-28.

Crepon, A., A. Hughes, P. Lee and J. Mairesse. (1998). “Research, innovation and productivity: an econometric analysis at the firm level", Economics of Innovation and New Technology, Vol. 7; 115–158.

Crespi, G., C. Criscuolo and J. Haskel. (2007). "Information Technology, Organizational Change and Productivity Growth: Evidence from UK Firms", London School of Economics and Political Science, Centre for Economic Performance 783.

Crespi, G., C. Criscuolo, J. Haskel and M. Slaughter. (2008). "Productivity Growth, Knowledge Flows, and Spillovers", NBER Working Papers 13959.

Crespi, G., L. Figal Garone, A. Maffioli and E. Stein. (2020). "Public support to R&D, productivity, and spillover effects: Firm-level evidence from Chile," World Development, Elsevier, Vol. 130(C).

Crouzet, N., J. C. Eberly, A. L. Eisfeldt, and D. Papanikolaou. (2022). "The Economics of Intangible Capital." Journal of Economic Perspectives, Vol. 36(3); 29-52.

Frazer, G. (2001). Linking Firms and Workers: Heterogeneous Labor and Returns to Education. Yale University.

Galindo-Rueda, F. and F. Verger. (2016). "OECD Taxonomy of Economic Activities Based on R&D Intensity". OECD Science, Technology and Industry Working Papers 2016/04.

García, J, M. (2022). "Estimación del impacto del uso de las TIC y de la inversión en I&D sobre la productividad de las empresas manufactureras en Perú", Nota técnica Banco Interamericano de Desarrollo IDB-TN-2590.

Groysberg, Boris, A. N. McLean, and N. Nohria. (2006). "Are Leaders Portable?", Harvard Business Review, Vol. 84(5); 92–100.

Griliches Z., (1979), "Issues in Assessing the Contribution of R&D to Productivity Growth", Bell Journal of Economics, Vol. 10(1); 92-116.

Griliches, Z, and T. Klette. (1996). "The Inconsistency of Common Scale Estimators When Output Prices Are Unobserved and Endogenous", Journal of Applied Econometrics, Vol. 11(4); 343-61.

Jaffe, A.B. (1989). "Real Effects of Academic Research", American Economic Review Vol. 79(5); 957-970.

Hall, B., and J. Mairesse (1995). "Exploring the Relationship Between R&D and Productivity in French Manufacturing Firms", Journal of Econometrics, Vol. 65; 263-293.

Hall, B, J. Mairesse, and P. Mohnen. (2010). Measuring the Returns to R&D, Chapter 24 in Handbook of the Economics of Innovation, Vol; 21033-1082.

Haskel, J. and S. Westlake. (2018). Capitalism without Capital: The Rise of the Intangible. Princeton University Press.

Instituto Nacional de Estadística e Informática del Perú (2023). Instituto Nacional de Estadística e Informática del Perú. https://www.gob.pe/inei/

Kerr, W. (2008). "Ethnic Scientific Communities and International Technology Diffusion", Review of Economics and Statistics Vol. 90(3); 518–537.

Kline, P., N. Petkova, H. Williams and O. Zidar. (2018). "Who Profits from Patents? Rent-Sharing at Innovative Firms", NBER Working Paper Series 25245.

Konings, J. and S. Vormelingen. (2015). "The Impact of Training on Productivity and Wages: Firm-Level Evidence", The Review of Economics and Statistics, Vol. 97(2); 485-497.

Levinsohn, J. and A. Petrin. (2003). "Estimating Production Functions Using Inputs to Control for Unobservables", Review of Economic Studies Vol. 70(2); 317–342.

Mairesse, J., and B. Hall. (1994). Estimating the Productivity of R&D in French and U.S. Manufacturing Firms: An Exploration of Simultaneity Issues With GMM, in International Productivity Comparisons, Ed. By K. Wagner. Elsevier-North.

Marilanta, M., P. Mohnen and P. Rouvinen. (2009). "Is Inter-Firm Labor Mobility a Channel of Knowledge Spillovers? Evidence From a Linked Employer-Employee Panel", Industrial and Corporate Change, Vol. 18(6); 1161–1191.

Marschak, J. and W. Andrews. (1944). "Random Simultaneous Equations and the Theory of Production," Econometrica, Vol. 12(3-4); 143-205.

Mincer, J. (1974). Schooling, Experience, and Earnings. New York: Columbia University Press for the National Bureau of Economic Research.

Moen, J. (2005). "Is Mobility of Technical Personnel a Source of R&D Spillovers?", Journal of Labor Economics, Vol. 23(1); 81-114.

Olley, G. S., and A. Pakes. (1996). "The Dynamics of Productivity in the Telecommunications Equipment Industry", Econometrica, Vol. 64; 1263–1297.

Ornaghi, C. (2006). "Spillovers in product and process innovation: Evidence from manufacturing firms", International Journal of Industrial Organization, Vo. 24; 349 – 380.

Romer, P. M. (1989). "Endogenous Technological Change", NBER Working Paper 3210.

Rovigatti, G. and V. Mollisi (2018). "Theory and practice of total-factor productivity estimation: The control function approach using Stata". The Stata Journal 18, Number 3, pp. 618-662.

Smith, M., D. Yagan, O. Zidar, and E. Zwick. (2019). "Capitalists in the Twenty-First Century." Quarterly Journal of Economics, Vol. 134(4); 1675–1745.

Tambe, P., L. Hitt, D. Rock and E. Brynjolfsson. (2020). "Digital capital and superstar firms", NBER Working Paper 28285.

Van Reenen, J. (1996)." The Creation and Capture of Rents: Wages and Innovation in a Panel of UK Companies", The Quarterly Journal of Economics, Vol.111(1); 195-226.

Weber, S. (2010). "Bacon: An effective way to detect outliers in multivariate data using Stata (and Mata)", The Stata Journal, Vol. 10(3); 331–338.

Zwick, T. (2006). "The Impact of Training Intensity on Establishment Productivity", Industrial Relations: A Journal of Economy and Society, Vol. 45; 26–46.

Diverse knowledge for diverse innovation; evidence from Chilean firms

Conocimientos diversos para innovaciones diversas, evidencia de firmas chilenas.

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Abstract

Using the Chilean Innovation Survey for 2019-2020, this work studies the effects of different knowledge sources on a range of innovation outputs. Findings reveal distinct impacts of sourcing information from competitors, customers, and government agencies on product, process, marketing, organizational, and social innovation outputs. Information from customers has a positive effect on overall innovation. Social innovation is positively influenced by information sourced from government agencies. These findings contribute to the understanding of how different knowledge sources shape innovation outputs on developing countries. They provide valuable insights for firms, policymakers, and researchers seeking to enhance innovation capabilities and inform evidence-based policies.

Key words: *Innovation output, Diverse knowledge sources, Chilean Innovation survey, Binary instrumental variable model.*

JEL Classification: *O31, O32, D22.*

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Resumen

Utilizando la Encuesta de Innovación de Chile para 2019-2020, este trabajo estudia los efectos de diferentes fuentes de conocimiento en una variedad de resultados de innovación. Los hallazgos revelan distintos impactos de la obtención de información de competidores, clientes y agencias gubernamentales en los resultados de innovación social, organizacional, de marketing, de procesos y de productos. La información de clientes tiene un efecto positivo en la innovación general. La innovación social se ve influenciada positivamente por la información procedente de agencias gubernamentales. Estos hallazgos contribuyen a comprender cómo las diferentes fuentes de conocimiento dan forma a los resultados de la innovación en los países en desarrollo. Proporcionan información valiosa para empresas, formuladores de políticas e investigadores que buscan mejorar las capacidades de innovación e informar políticas basadas en evidencia.

Palabras clave: *Resultados de innovación, Diversas fuentes de información, Encuesta de innovación chilena, Modelo de variable instrumental binaria.*

Clasificación JEL: *O31, O32, D22*

1. Introduction

Innovation has long been recognized as a crucial driver of economic growth and competitiveness. As societies and economies become increasingly complex and interconnected, the ability of firms to adapt and innovate becomes ever more essential. Understanding the factors that contribute to successful innovation is therefore of paramount importance for policymakers, researchers, and business leaders alike. It has been widely acknowledged that firms need to look beyond their internal resources and tap into external knowledge to foster innovation. However, the specific mechanisms through which diverse knowledge sources influence innovation outcomes require further investigation.

Over the years, scholars have made significant progress in developing models to comprehend the dynamics of innovation. Data collected through innovation surveys has played a pivotal role in unraveling the causality behind innovation success. By examining various firm-level variables, such as research and development (R&D) expenditure, human capital, sales, and total employees, researchers have sought to identify the determinants of innovation output.

However, a fundamental question remains: Are there specific variables that have distinct impacts on specific types of innovation outputs? To shed light on this matter and disentangle the intricate causal relationships behind innovation success, it is crucial to develop robust models that consider bidirectional effects. The more we understand which factors contribute to specific types of innovation, the better equipped we are to formulate effective government policies that promote desirable outcomes for local economies, particularly in developing countries.

While previous studies have shed light on the effects of knowledge sources on innovation performance in various contexts, there is a need to explore these issues within the unique context of Chilean firms. Chile is a dynamic and emerging economy that has made significant efforts to foster innovation and entrepreneurship. Therefore, examining the role of diverse knowledge in Chilean firms' innovation outputs can provide a broader understanding of innovation dynamics in emerging economies.

Building upon the seminal work of Cohen and Levinthal (1990), this paper focuses on the firm's capacity to acquire and utilize information from diverse sources as a critical determinant of innovation. Recognizing the importance of addressing endogeneity concerns, our approach draws inspiration from the work by Crepon, Duguet, and Mairesse (1998).

The primary objective of this paper is to estimate an empirical model that reveals the causal relationships between different types of information sources and various forms of innovation output. To accomplish this, we leverage reliable innovation survey data collected in Chile during the period of 2019-2020. Our model considers the evolution of empirical research on the determinants of innovation output and employs instrumental variables to estimate a binary treatment model with idiosyncratic average effects.

Our findings demonstrate that the utilization of diverse innovation information sources has varying impacts on different types of innovation outputs, each with its unique magnitude. Notably, while information sourced from customers positively influences most types of innovation, we found no discernible effect from information obtained from competitors. Furthermore, government information emerges as a particularly valuable resource, benefiting social innovation significantly while also exhibiting positive effects on process and organizational innovations.

By shedding light on the intricate relationships between information sources and innovation outputs, this study provides valuable insights for policymakers, researchers, and firms seeking to enhance their innovation capabilities. The empirical evidence presented herein serves as a foundation for evidence-based policy recommendations aimed at fostering specific types of innovation that can drive the local economies of developing countries forward.

Overall, this research contributes to the existing literature by offering a comprehensive analysis of the role of diverse knowledge in driving diverse innovation outcomes. By highlighting the nuanced relationships between information sources and innovation outputs, we aim to stimulate further research and inform strategic decision-making processes in both the public and private sectors.

The rest of this paper is structured as follows. Section 2 presents a literature review with previous findings in the topic of this work. Section 3 proposes a theoretical model by which the variables are related. Section 4 presents the database while section 5 presents the empirical strategy. Results are discussed on section 6 and section 7 concludes with a discussion about the value of our findings.

2. Previous Literature

RESEARCH ON INNOVATION PERFORMANCE

This literature review firstly highlights the importance of investigating innovation performance and its determinants in various contexts. Understanding the factors that contribute to successful innovation outcomes is crucial for firms and policymakers alike. By reviewing previous studies on innovation performance, this paper aims to contribute to the existing body of knowledge by examining the role of diverse knowledge in fostering innovation, specifically focusing on evidence from Chilean firms.

By examining the literature on innovation performance, this paper aims to discuss the importance of external knowledge, ownership structure, organizational practices, sectoral differences, customer participation, and the effectiveness of different knowledge sources in driving innovation. Understanding these factors can help firms and policymakers develop strategies and policies that promote innovation and enhance overall economic performance.

Numerous studies have focused on investigating innovation performance and its determinants. Crepon, Duguet, and Mairesse (1998) developed a model that established a framework for exploring the causation of innovation output and productivity growth by linking innovation survey variables. Building on this model, subsequent research has further examined the relationship between innovation survey variables and innovation output.

The importance of external knowledge for innovation has been emphasized in various studies. Sofka and Grimpe (2010) argued that firms should develop strategies to leverage external information, and the success of this strategy significantly influences innovation outcomes. They demonstrated that combining in-house R&D investments with a market-oriented search strategy enhances the effectiveness of innovation efforts.

Ownership structure has also been identified as a factor influencing innovation performance. Choi, Lee, and Williams (2011) found that firms with foreign ownership have a higher probability of successful innovation. Their study, conducted on Chinese firms, revealed that foreign ownership and affiliation with a business group strongly influence the volume of patent registrations. This suggests that ownership structure plays a vital role in determining innovation outcomes.

Organizational practices have been recognized as crucial factors for innovation success. Mol and Birkinshaw (2014) highlighted the significance of certain organizational practices in fostering innovation. They emphasized the role of external involvement in the innovation management process, which not only provides direct input from external change agents but also brings prior external experience as an internal agent of change.

Analyzing sectoral differences in innovation outcomes is also important. Castellacci (2008) presented a sectoral taxonomy that integrated manufacturing and service industries within a comprehensive framework. This approach underscored the increasing importance of vertical linkages and inter-sectoral knowledge exchanges between these interconnected branches of the economy. Božić and Mohnen (2016) conducted a quantitative analysis using Croatian Community Innovation Survey data and found that while there are some differences, service and manufacturing SMEs share similar determinants of innovation activities. However, service SMEs rely more on acquired knowledge compared to their manufacturing counterparts.

The relationship between customer participation and innovation performance has been explored in several studies. Chang and Taylor (2016) conducted a meta-analysis that examined the effects of contextual factors on the relationship between customer participation and new product development performance. Their analysis revealed that involving customers in the ideation and launch stages of new product development improves new product financial performance directly, as well as indirectly through accelerated time to market. However, customer participation in the development phase slows down time to market, leading to a deterioration in new product financial performance.

The study by Anzola-Román, Bayona-Sáez, and García-Marco (2018) investigated the influence of internal and externally sourced innovation practices on the likelihood of achieving product and process innovations. Their findings indicated positive effects of internal R&D and externally sourced innovation practices, as well as a positive influence of organizational innovation on the realization of technological innovations.

Understanding the most effective sources of innovative ideas remains a significant challenge in technological innovation management. Criscuolo et al. (2018) examined the effectiveness of different combinations of knowledge sources for achieving innovative performance. Their study, based on a large-scale sample of UK firms, revealed important differences between product and process innovation, with broader knowledge searches associated with the former.

THE MANAGEMENT OF INNOVATION AND FIRM PERFORMANCE

Innovation is widely recognized as a crucial driver of firm success, contributing to competitive advantage, market growth, and long-term sustainability. As the business landscape becomes increasingly dynamic and complex, organizations must continuously adapt and innovate to stay ahead. Consequently, understanding firm management factors that influence innovation performance has become a topic of great interest for researchers and practitioners alike.

Cohen and Levinthal (1990) highlighted the concept of absorptive capacity, which refers to a firm's ability to acquire, assimilate, and utilize external knowledge to foster innovation. They emphasized that prior knowledge and experiences significantly influence a firm's absorptive capacity. This perspective underscores the importance of leveraging diverse knowledge sources and learning from external information to enhance innovation capabilities. By exploring the relationship between diverse knowledge and innovation outcomes, valuable insights can be gained into how firms can effectively tap into a range of knowledge domains.

While much of the existing literature has primarily focused on product and process innovation, there is a growing recognition of other dimensions of innovation that extend beyond tangible outputs. These dimensions include management, organizational, and social innovations, which encompass novel practices, structures, and techniques that advance organizational goals. OECD/Eurostat (2018) proposed a comprehensive framework encompassing these various innovation types. Acknowledging and exploring these diverse dimensions of innovation contribute to a more comprehensive understanding of the innovation process and its impact on firm performance. Chen, Wang, and Huang (2019) investigated the relationship between organizational innovation and technological innovation capabilities, exploring their impact on firm performance. Through structural equation modeling, their study revealed that innovation capabilities partially mediate the link between organizational innovation and firm performance.

Furthermore, effective innovation management practices play a vital role in realizing the full potential of innovation. Birkinshaw and Mol (2008) identified four key processes—motivation, invention, implementation, and theorization and labeling—that collectively shape management innovation. By examining the roles of change agents within and outside the organization, valuable insights can be gained into how innovation management practices can be optimized to maximize the benefits derived from innovation efforts.

However, despite the recognized importance of innovation and its multidimensional nature, challenges persist in realizing significant economic returns from innovation. Teece (1986) highlighted that profits often accrue to complementary asset owners, customers, and imitators rather than to the original developers of intellectual property. This raises important questions regarding the alignment of innovation strategies with appropriate management practices to ensure that firms capture and capitalize on the economic benefits of their innovative endeavors.

Given the multifaceted and ongoing nature of innovation, it is essential to delve into the literature to gain a comprehensive understanding of the relationship between diverse knowledge and diverse innovation outcomes. By exploring the interplay between absorptive capacity and different dimensions of innovation, in the context of effective innovation management practices, this study aims to provide evidence on the relationship between diverse knowledge and diverse innovation outcomes among Chilean firms. Through this investigation, valuable insights can be obtained to inform firms' innovation strategies and enhance their ability to drive successful innovation outcomes while realizing economic returns.

INFORMATION SOURCES AND INNOVATION

The study of information sources and their impact on firm-level innovation performance is highly motivated by the recognition of innovation as a critical driver of firm success. In today's competitive business environment, firms are constantly seeking ways to improve their innovation capabilities and outcomes. Understanding the role of information sources in this process is essential for firms aiming to leverage knowledge effectively and achieve sustainable innovation performance.

Previous research has shed light on the influence of different types of information sources on innovation. Arvanitis, Lokshin, Mohnen, and Wörter (2013) conducted a study based on panels of Dutch and Swiss innovating firms, finding that both "buying" and "cooperating" have a positive effect on innovation. However, simultaneous utilization of these information sources does not necessarily lead to higher innovation performance. Pejić Bach et al. (2015) emphasized the catalytic role of information sources in innovation improvement, utilizing CIS data from Croatia, France, and the Netherlands. Their findings indicated that internal sources, customers, suppliers, and universities are important information sources for both internal and external R&D activities across the three countries. Interestingly, firms from the Netherlands exhibit different patterns in utilizing information sources, relying more on competitors compared to firms from Croatia and France. Additionally, government information sources had a relatively smaller impact on firms' innovation performance.

The distinction between internal and external sources of information has been explored in relation to the generation of product and process innovation. Gómez, Salazar, and Vargas (2016) examined the usage of internal and external sources of information by Spanish firms, including customers, suppliers, competitors, consultants, and universities. They found that the importance of external sources of information varies depending on the type of innovation considered. For process innovation, firms mainly rely on suppliers, while for product innovation, the main contribution comes from customers. Damanpour, Sanchez-Henriquez, and Chiu (2018) investigated the dual role of internal and external sources of knowledge and information in the adoption of managerial innovations. Their findings indicated that internal implementation actions have a stronger effect than external implementation actions in influencing innovation adoption. Dotzel and Faggian (2019) analyzed the relationship between external knowledge sourcing and various innovation outcomes in rural and urban establishments in the U.S. Their results suggested that external knowledge sourcing specifically promotes product, process, and green innovation in U.S. firms. They also highlighted the potential importance of knowledge sourcing from non-local organizations, particularly in supporting innovation in rural markets compared to urban markets.

Furthermore, the literature has explored the effects of different combinations of knowledge sources on innovation output. Basit and Medase (2019a) highlighted the positive link between knowledge diversity and firm-level innovation performance, emphasizing the importance of knowledge from customers in the private and public sectors, as well as knowledge from competitors. Basit (2021) extended this research by examining the impact of external knowledge sources on the willingness of small and medium-sized enterprises (SMEs) to introduce organizational innovation, revealing the greater importance of external knowledge for small firms and their propensity to utilize diverse sets of external knowledge.

By delving into the literature on information sources and innovation, it becomes evident that diverse knowledge utilization plays a vital role in driving firm-level innovation performance. The interplay between different types of information sources, whether originating from paid deals or cooperation agreements, and whether derived from internal or external agents, offers valuable insights for firms aiming to enhance their innovation capabilities and achieve superior innovation outcomes. Therefore, this study seeks to contribute to the existing body of knowledge by examining the relationship between diverse knowledge sources and diverse innovation outcomes within the context of

Chilean firms.

ENDOGENEITY OF R&D ON INNOVATION OUTPUTS

Understanding the relationship between research and development (R&D) investment and innovation outputs is crucial for firms aiming to enhance their innovation performance. R&D plays a vital role in driving innovation, but the nature of the interrelation between R&D inputs and innovation outputs is complex and multifaceted. By examining the endogeneity of R&D investment on innovation outputs, researchers seek to disentangle the causal relationship between these variables and provide valuable insights into the effectiveness of R&D strategies in fostering innovation.

Several studies have addressed the endogeneity of R&D investment on innovation outputs using various econometric approaches. Crepon, Duguet, and Mairesse (1998) conducted an analysis at the firm level, focusing on French manufacturing firms. Their study employed a system of simultaneous equations to examine the interplay between productivity, innovation, and R&D. They proposed an econometric method to address selectivity and simultaneity biases, which has subsequently been adopted by numerous researchers using data from different countries.

Piga and Vivarelli (2004) emphasized the connection between R&D investment and the decision to carry out innovations. They employed an empirical approach that enabled a joint analysis of the determinants of these two decisions while correcting for sample selectivity. Their study shed light on the intertwined relationship between R&D investment and innovation activities.

Mairesse and Mohnen (2004) utilized an instrumental variable approach to evaluate the contribution of R&D to innovation. Their research developed a generalized Tobit model based on the notion that firms engaging in R&D are more likely to be selected from those that produce some innovative outcomes. This approach also provided insights into the effectiveness of R&D in driving innovation.

In line with addressing endogeneity and selectivity issues in estimating the effects of R&D on innovation outputs, Basit and Medase (2019b) adopted a binary instrumental variable approach. Their study focused on the relationship between R&D investment and firm-level innovation performance, utilizing microdata from the German Community Innovation Survey 2013. By employing instrumental variable techniques, they were able to overcome potential biases and obtain more reliable estimates of the effects of R&D on innovation outputs.

By exploring the literature on the endogeneity of R&D on innovation outputs, researchers aim to disentangle the complex relationship between these variables. The use of econometric methods, such as simultaneous equation models, instrumental variable approaches, and correction for sample selectivity, provides valuable insights into the effectiveness of R&D strategies in driving innovation outcomes. These methods also serve as a starting point to study the effects of additional variables such as information sources on innovation outputs.

3. Theoretical Model

To develop the model, this study first considers the relationship between research and development (R&D) and innovation outcomes. It is widely recognized in the literature that R&D is a key determinant of innovation output. Harris and Moffat (2011) highlight that previous studies have provided empirical evidence and justifications for this relationship, considering R&D as an input in the production function of innovation. This notion has been discussed and examined from various perspectives with diverse datasets since Geroski's work in 1990. Building upon Schumpeter's idea that R&D is driven by entrepreneurship with the objective of gaining market power through innovation. Harris and Trainor (1995) empirically analyzed this concept. They proposed that entrepreneurs are the ones who invest in R&D, motivated by the desire to generate innovations.

Mairesse and Mohnen (2002) conducted a preliminary analysis of the first Community Innovation Survey, leading them to conclude that research and innovation activities play a fundamental role in knowledge-based economies. Their findings suggest that new knowledge is a key driver of firm innovation and growth. Furthermore, they highlight the importance of research that integrates innovation and production accounting frameworks in a systematic manner, as it can significantly contribute to understanding the complex relationship between R&D and innovation output.

The theoretical modeling in this study draws upon the idea put forth by Crepon, Duguet, and Mairesse (1998) that innovation output is the result of R&D investment, human capital intensity, variables associated with the market, and information sources. It is important to note that R&D is not assumed to be exogenous but rather partially endogenous, as argued in their paper and supported by other sources in the literature.

Previous studies have shown a positive relationship between human capital intensity, R&D investment, and innovation output. In a recent work, Medase (2019a) suggested that product, process, marketing, and organizational innovation can be attributed to R&D investment and human capital, with different information sources exerting varying effects on different types of innovation outputs. Specifically, Medase (2019b) focused on knowledge flows from customers and competitors and found that different innovation information sources influence different categories of innovation.

Building on the existing literature, we propose a basic model wherein innovation is contingent upon R&D investment, human capital, knowledge sources, and various additional moderating and control variables, such as size and economic sector indicators. To comprehensively capture the multifaceted nature of innovation outputs, this study introduces a multinomial model. Within this framework, the determination of innovation output is influenced by R&D investment, human capital intensity, innovation information sources, and a set of control variables. The specific components of the model are outlined as follows:

(1) $$\mathrm{I}_{\mathrm{i}} = \alpha + \mathrm{x}_{\mathrm{i}} \beta_{1} + \mu_{\mathrm{i}}$$

Where $x_i = \left(R\,\&\,D_i, HC_i, OtherInv_i, Emp_i, Inf_i^1, Inf_i^2, Inf_i^3, Act_i^1, \ldots, Act_i^n \right)$

With R_i is R&D investment, $OtherInv_i$ is funding of other innovative investment activities including acquisition of knowledge, machinery and training, HC_i is human capital intensity, Emp_i is the log of the number of employees or a measure of firm size, Inf_i^1 is a dummy indicating whether or not the source of ideas for innovation developed with information from competitors, Inf_i^2 is a dummy indicating whether or not the source of ideas for innovation developed with information from customers, Inf_i^3 is a dummy indicating whether or not the source of ideas for innovation developed with information from government agencies, and $Act_i^1, \ldots, Act_i^n$ are economic sector dummies.

4. Data

The study of innovation determinants and the relationship between firm characteristics, innovation inputs, and innovation outputs, based on innovation survey data and econometric research, has been extensively conducted over the past three decades. Mairesse and Mohnen (2010) provided an overview of the history, evolution, and content of innovation surveys, discussing the characteristics of the data they encompass and the challenges they pose to analysts and econometricians. The authors also documented the two primary purposes for which these data have been utilized: the construction of scoreboards for monitoring innovation and scholarly analysis of various issues related to innovation. A significant portion of the literature employing innovation survey data has focused on examining the determinants, effects, complementarities, and dynamics of innovation.

For the empirical analysis in this study, micro-level data from the Chilean

National Innovation Survey (ENI) 2019-2020 were utilized. The database is made from a probabilistic design (representative of all those companies registered in the Chilean Tax Service (SII) and sales of USD$100,000 per year. The survey comprises a sample of 5,790 firms, which is representative of a universe of 190,084 Chilean firms across all economic sectors, including Manufacturing, Mining, Energy, and Services. The survey has been conducted since 1995, and its questionnaire aligns with the guidelines outlined in the fourth edition of the Oslo Manual OECD/EUROSTAT (2018).

The National Innovation Survey (ENI) aims to provide information on the structure of the innovation process of companies in Chile (inputs and results) and to show the relationships between said process and the innovation strategy of companies, the innovative effort, the factors that influence their ability to innovate and the economic performance of companies.

ENI measures variables such as the type of innovation (product and business processes), degree of novelty, intellectual property rights, innovative activities (including research and development, R&D), carried out by Chilean companies in different economic sectors and regions of the country. The survey also captures information on firm characteristics, sales, exports, employment by education levels, innovation output, information sources, other innovative investments, R&D activities, R&D cooperation, and innovation obstacles. Notably, the Chilean Innovation Survey also captures non-technological innovation, such as marketing, organizational, and social innovation.

The database is structured in thirteen modules that firstly describe product and different kinds of process innovation and their effects at the firm level. It then measures social innovation and different sorts of innovation spending including R&D, though data with the detail of R&D spending and funding is collected in a separate R&D survey. A following section of the survey collects data on information sources and cooperation activities regarding innovation efforts. It also contains a module on human resources dedicated to innovative or innovation related activities, followed by a module that describes whether firms obtained innovation funding from a series of public programs. Finally, the survey structure includes innovation obstacles, intellectual property rights and perspectives for future firm innovation.

Table 1 presents a comprehensive description of the variables employed in this research. The database contains valid information for 5,519 observations. The average firm in the database has a 21% likelihood of achieving at least one type of innovation. Among the various types of innovation, process innovation is the most prevalent, with the average firm having 18% probability of reporting its implementation during the period 2019-2020. Product and organizational innovations follow closely, reported by 10% and 9% of firms, respectively, while social innovations were achieved by only 3% of the sampled firms. Average firms have a 9% probability of investing io R&D during the period, while they are more likely to engage in other innovative investments including machinery, training, and knowledge acquisition. The probability of using information from customers is 8%, followed by government sources, and lastly, competitor sources. On average, 28% of employees possessed a professional degree or higher level of education. Less than 8% of the firms in the sample exported more than USD$500,000, and only 3% of the firms received public funds for innovation activities.

The variable description is summarized on Table 2. All these variables are self-reported and correspond to the survey responses provided by firms' managers. Most of the variables used are binary variables because they express whether the firm has declared to have performed or achieved a specific action over the period 2019-2020. The variable log of the numbers of employees, on the other side is continuous and is intended to reflect the size of the firm.

Table 3 presents the correlation matrix of the main variables. The correlation results demonstrate that firm-level resources, innovation inputs, and innovation output variables exhibit the expected signs. The instrumental variables, high exports, and public innovation funding, exhibit a significantly higher correlation with the instrumented variable R&D activity compared to their correlation with the dependent variables of innovation outputs.

TABLE 1
SUMMARY STATISTICS

Variable	Observations	Mean	Std. Dev.	Min	Max
1. Any Innovation	5519	0,207	0,405	0	1
2. Product Innovation	5519	0,101	0,301	0	1
3. Process Innovation	5519	0,185	0,388	0	1
4. Marketing Innovation	5519	0,061	0,239	0	1
5. Organizational Innovation	5519	0,091	0,288	0	1
6. Social Innovation	5519	0,031	0,174	0	1
7. R&D Activity	5519	0,087	0,282	0	1
8. Other Innovative Investments	5519	0,155	0,362	0	1
9. Source Competitors	5519	0,004	0,067	0	1
10. Source Clients	5519	0,082	0,274	0	1
11. Source Government	5519	0,020	0,140	0	1
12. Highly Educated	5519	0,281	0,328	0	1
13. Log Total Employees	5519	3,100	1,714	0	9,89
14. Exports USD$500.000+	5519	0,076	0,265	0	1
15. Public Inn. Funding	5519	0,034	0,182	0	1

Source: Own calculations based on the Chilean Innovation Survey 2019-2020.

TABLE 2

DESCRIPTION OF VARIABLES

Variable Name	Type	Description
Any innovation	Dummy	1 if the firm introduced any innovation in 2019-2020 and 0 otherwise
Product innovation	Dummy	1 if the firm introduced new or significantly improved product or service in 2019-2020 and 0 otherwise
Process innovation	Dummy	1 if the firm introduced new or significantly improved operational processes in 2019-2020 and 0 otherwise
Marketing innovation	Dummy	1 if the firm introduced marketing innovation (i.e. significant modification in design or packaging of goods or services) in 2019-2020 and 0 otherwise
Organizational innovation	Dummy	1 if the firm introduced organizational innovation (i.e. new business practices for organizing procedures) in 2019-2020 and 0 otherwise
Social innovation	Dummy	1 if the firm introduced social innovation in 2019-2020 (i.e. sustainable innovation) and 0 otherwise
Internal R&D	Dummy	1 if the firm carried out internal R&D activities
Other Innovative Investments	Dummy	1 if the firm carried out investments
Source of knowledge from competitors	Dummy	1 if the firm get information source for new ideas in current innovation projects from the competitors in 2019–2020 and 0 otherwise
Source of knowledge from the customers	Dummy	1 if the firm get information source for new ideas in current innovation projects through the customers sector in 2019–2020 and 0 otherwise
Source of knowledge from the government	Dummy	1 if the firm get information source for new ideas from interaction with government agencies in 2019-2020 and 0 otherwise
Graduate employees	Continuous standardized to 0-1	Number of graduate employees (professional, master or PhD) to the total number of employees in 2020.
Employment	log	The log of the number of employees as a measure of firm size
High Exports	Dummy	1 if exports were higher than USD$500,000 over 2019-2020 and 0 otherwise.
Public Funding	Dummy	1 if firm received innovation funding from the public sector in 2019-2020 and 0 otherwise
$Act_i^1,\ldots,Act_i^{13}$	Dummy	1 if firm belongs to specific sector and 0 otherwise

Source: Variables defined based on data from the Chilean Innovation Survey 2019-2020.

TABLE 3

CORRELATION MATRIX

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Any Innovation	1,00														
2. Product Innovation	0,66	1,00													
3. Process Innovation	0,93	0,51	1,00												
4. Marketing Innovation	0,50	0,37	0,53	1,00											
5. Organizational Innovation	0,62	0,36	0,66	0,52	1,00										
6. Social Innovation	0,32	0,31	0,28	0,22	0,24	1,00									
7. R&D Activity	0,52	0,48	0,46	0,30	0,32	0,31	1,00								
8. Other Innovative Investments	0,76	0,53	0,72	0,40	0,47	0,29	0,46	1,00							
9. Source Competitors	0,12	0,12	0,13	0,11	0,10	0,09	0,17	0,14	1,00						
10. Source Clients	0,54	0,54	0,49	0,41	0,37	0,27	0,49	0,59	0,20	1,00					
11. Source Government	0,25	0,23	0,22	0,16	0,18	0,24	0,31	0,26	0,31	0,29	1,00				
12. Highly Educated	0,12	0,14	0,11	0,07	0,09	0,08	0,12	0,09	0,04	0,10	0,08	1,00			
13. Log Total Employees	0,19	0,13	0,17	0,08	0,14	0,09	0,22	0,18	0,07	0,13	0,08	-0,20	1,00		
14. Exports USD$500.000+	0,12	0,10	0,08	0,06	0,07	0,06	0,19	0,10	0,05	0,10	0,07	0,00	0,33	1,00	
15. Public Inn. Funding	0,22	0,22	0,19	0,10	0,15	0,17	0,32	0,23	0,07	0,19	0,24	0,09	0,04	0,05	1,00

Source: Own calculations based on the Chilean Innovation Survey 2019-2020.

5. Empirical Strategy

To empirically estimate the theoretical model, our first step is to examine the presence of endogeneity related to a selectivity problem. The literature provides several compelling reasons why innovation could also influence R&D, which have been well-documented. Mansfield (1969) presented one of the earliest works on this relationship, arguing that successful innovation increases a firm's technological opportunities, making further innovation efforts more likely.

Another argument for the impact of innovation on R&D is the difficulty firms may face in obtaining funding for innovation projects from external sources due to their inherent riskiness (Peters, 2009). If successful innovations lead to increased profitability and access to external funding, firms are more likely to engage in further R&D.

Furthermore, the relationship between innovation, exporting, and R&D has been discussed as a bidirectional force by Harris and Moffat (2011). Some studies have emphasized the persistence of innovation and its positive impact on subsequent R&D investment. Geroski et al. (1997) and Malerba and Orsenigo (1999) have also explained the mechanism through which innovation influences R&D.

From the literature, it can be concluded that the determinants of R&D expenditure for an individual firm are not completely independent of the firm's probability of innovating. Innovating firms allocate resources to R&D to achieve innovations, while non-innovating firms may invest in R&D to enhance their absorptive capacities. Additionally, the variables that explain R&D may differ depending on whether the firm is innovating or not. Hence, there is a selectivity problem.

To address the selectivity problem, one perspective is to consider innovation as an auto-selection process. Expected R&D investment depends on the firm's innovation status, making the selectivity problem more complex than a simple sample selectivity bias. Kriaa and Karray (2010) suggest that one approach to solving this problem is to limit observed heterogeneity between firms while also controlling for unobserved heterogeneity. Other researchers have used an approach based on Heckman (1979) to address selectivity problems in this model. Following Basit and Medase (2019b), this work adopts an instrumental variable (IV) binary treatment model with a selection equation based on a set of instruments as the empirical methodology.

The econometric model aims to study the relationship between firm-level innovation, human capital, internal R&D activities, and sources of knowledge flows. Given the binary nature of the endogenous and instrumental variables, this study employs an IV binary treatment model. The estimation method is a two-stage Heckman binary treatment model. This empirical setup allows us to address potential endogeneity problems. The binary treatment model used in this research has been thoroughly explained by Wooldridge (2010) and has been employed by authors such as Basit (2021) and Cerulli (2012). The two-stage Heckman binary treatment model with heterogeneous treatment response helps to address the endogeneity issues that arise in this context, where the relationship between innovation output and performance differs between firms investing in R&D and those that do not.

The specification of the instrumental variable model is as follows:

(2) $$y = \mu_0 + \propto w + x\beta_0 + w\left(x - \mu_x\right)\beta + e_0 + w\left(e_1 - e_0\right)$$

Where we assume that observable and unobservable heterogeneity are not the same, so $\left(e_1 \neq e_0\right)$. Following the principle of the two-stage sample selection estimation of Heckman (1979), we assume that on a binary treatment model we can still observe normality of the error term. This way we use a general model firstly specifying a fundamental regression.

(3) $$y_i = x_i\beta + \mu_{1i}$$

Where selection implies that the dependent variable is known under the condition that

$$z_i\delta + \mu_{2i} > 0$$

Where $\mu_1 \sim N\left(0,\sigma\right)$, $\mu_2 \sim N\left(0,1\right)$, $and\ Corr\left(\mu_1,\mu_2\right) = \rho$. And if we could assume that $\rho = 0$, we could ignore the selection problem.

The strategy then implies the estimation of two equations, the main equation with innovation output as dependent variable, and a selection equation with R&D dummy as a dependent variable. Innovation output is a set of dummy variables that can describe each type of innovation separately with:

(4) $$INN_i = \alpha + x_i\beta_1 + R\,\&\,D_i\beta_2 + \mu_i$$

where: $x_i = \left(InnAct_i, Inf_i^1, Inf_i^2, Inf_i^3, HC_i, Emp_i, Act_i^1, \ldots, Act_i^n\right)$, and:

(5) $$R\,\&\,D_i = \delta_1 + x_i\delta_1 + z_i\delta_2 + \mu_i$$

where: $$z_i = \left(HExp_i, PublicFunding_{i,}\right)$$

Where $InnAct_i$ is a dummy with value 1 if the firm has spent on any of the other non-R&D activities: machinery, knowledge acquisition, training. Inf_i^1

is a dummy indicating whether the source of ideas for innovation developed with information from competitors, Inf_i^2 is a dummy indicating whether the source of ideas for innovation developed with information from customers, Inf_i^3 is a dummy of whether the ideas for innovations came from government sources. HC_i is human capital intensity measured as highly educated employees divided by total employees, Emp_i is the log of the number of employees as a measure of firm size. $Act_i^1,\ldots,Act_i^n$ are economic sector dummies. For the first stage equation the instrumented variable $R\&D_i$ is a dummy equal to 1 if the firm has done R&D investment. We used two instruments that are statistically valid with significantly higher correlation to the instrumented variable compared to the endogenous variable[1]. The instruments are $HExp_i$ that is a dummy indicating whether exports were higher than USD$500,000, and $PublicFunding_{i,}$ that is a dummy equal to 1 if the firm received any kind of public funding for innovation during the period 2019-2020, and 0 otherwise. The instruments were chosen considering that both, access to exporting markets and access innovation public funding, are expected to have a greater impact over R&D efforts compared to innovation outputs because the latter result from a more complex knowledge generation processes that is affected by innovation efforts, information sources and firms' human capital.

6. Main Results

The findings of this paper are presented in this section. The estimation method begins with a set of preliminary binary probit regressions using 5,519 observations. This step is taken before considering any endogeneity problems.

Table 4 displays plausible results that align with the theoretical model. All types of innovation outputs considered in the model are positively and significantly influenced by both R&D investment and other innovative investments. The proportion of employees with a professional title or higher level of education also has a positive and significant impact on innovation output in all regressions. Firm size, measured as the logarithm of total employees, consistently shows a positive parameter in all regressions, although its impact appears to be lower compared to the other variables. Furthermore, firm size has a significant impact on process, organizational, and social innovation, but its significance is not observed in the case of product and marketing innovation. This preliminary result suggests that smaller firms may have the ability to achieve these types of innovation output without facing clear disadvantages due to their size.

1 See the correlation details on table 3

Based on these initial results, there is evidence that information from competitors may have very little or no impact on all types of innovation output. This result could be due to biases caused by endogeneity problems. It could also be attributed to the fact that a relatively small percentage of firms utilize information from competitors. Regarding sourcing innovation information from customers, the results indicate that it is an important and significant variable that positively affects all types of innovation outputs. This finding suggests that firms attach greater importance to customer feedback, indicating that customer-oriented firms are more likely to succeed in their innovative endeavors. This observation aligns with recent management literature that emphasizes the importance of focusing business models on customers. The regressions also reveal that sourcing information from government agencies is associated with specific types of innovation outputs. The results propose that government information has a significant impact only in the case of social innovations.

However, following our empirical strategy and in line with previous literature[2] on the estimation of innovation determinants, Table 5 examines the same question using a Heckman two-stage binary instrumental variable treatment model. This estimation method has been employed in other papers, including Basit and Medase (2019a, 2019b). The binary selection variable is R&D activity, and we use dummy variables as instruments to indicate whether exports exceed USD$500,000 and whether any public funding for innovation was received. Both instruments exhibit considerably higher correlation with the R&D activity dummy compared to innovation output variables. Like on the previous regressions, control variables for economic sector are included but not reported in the table.

First stage results are reported on the first column. Note that the first-stage equation is the same for all six innovation equations. We find that both instruments, exports and public funding have a positive and significant impact on R&D efforts at the firm level.

The results of the following columns suggest that innovative investments other than R&D is also a significant determinant of all types of innovation. The previous finding indicating a low and insignificant impact of information from competitors on innovation output is also supported by these results. Information from clients as a source for innovation ideas has a positive and significant effect in all cases except for social innovation, where government agencies emerge as the only important and significant information source. Government information also has a positive and significant impact on process and organizational innovation, albeit with smaller parameter sizes. The positive effect of the proportion of highly educated employees on different types of innovation

2 The argumento f why R&D should be considered endogenous on an Innovation equation is particularly well explaiden in the work by Crepon, Duguet and Mairesse (1998).

output is observed, although the effect is smaller than what was observed in the previous table and is not significant in the case of social innovation. The results also demonstrate that the logarithm of the total number of employees has a positive and significant impact on innovation outputs, except in the case of product and marketing innovation, which is consistent with the findings from the previous table.

For each of the second stage equations, the two-stage Heckman model estimates rho (actually, the inverse hyperbolic tangent of rho) that represents the correlation of the residuals in the two equations. Additionally, it presents the estimation of sigma (actually, the log of sigma) which represents the standard error of the residuals of the second stage equation. Lambda is rho*sigma, which is found to be significant on all but one of the equations which suggests that the estimation of R&D in the first equation is relevant for the estimation of the second stage equations for all kinds of innovation output except organizational innovation.

These results are relevant because, based on a previously validated empirical strategy[3] that takes endogeneity into account, they explain the importance of different information sources for the several distinct types of innovation outputs. The results show some similarity with previous works[4] regarding the importance of customer information for innovation output but also differ finding that for the case Chilean firms the importance of information from competitors is not an important determinant for innovation output. It could be the case that this result is observed because Chilean firms have a very low probability of sourcing innovation information from competitors, and hence there is not enough variation to find a significant parameter. In fact, only 0.4% of firms declared to have used information from competitors as a source of innovation ideas. Additionally, it could also be the case that the low use of competitor information is the result of low trust or higher levels of secrecy among industry-level competitors. In any case, this result calls for further research that can dig into industry-level information flows to explain this low frequency and low impact firm competitor relation.

But even though information from competitors has not proven to be relevant for innovation output, we found that innovation output among Chilean firms is driven to a large extent by market orientation, particularly by sourcing information from customers. In the line with the findings by Anzola-Román (2018), this result is important from a managerial point of view because it shows that considering customer data is an important driver of innovation success. Additionally, from the public policy perspective, this result implies the opportunity of developing public instruments to promote customer-firm inter-

3 Heckman (1979)

4 Basit and Medase (2019a, 2019b).

actions such as experimental fairs or targeted consumer surveys.

But the most relevant and novel result found on this work is related to the estimation of social innovation determinants. The work by Tortia et al (2020) discussed how social innovation interplays with entrepreneurship in public and private institutions. Social innovations imply the achievement of results that benefit socially vulnerable groups or the enviroment, it should be financially sustainable, and it functions based on the use of new approaches and ideas to solve a particular social problem.

We find that in terms of information sources, social innovation is mainly driven by information from government institutions, while customer and competitor sources are not relevant when the full model is estimated. This result, if confirmed by further research, could have important public policy implications. The work by Mulgan (2007) discussed that social innovation often involves universities, government agencies and private companies working together. He also showed that social innovation is more related to the combination of knowledge from different actors rather than the advancement of new technologies at the individual organizational level. Particularly, considering that social innovation has a large positive externality component, our results suggest that public funding instruments to promote collaboration with government institutions could help promote innovations that have the highest social value.

TABLE 4

PRELIMINARY BINARY PROBIT REGRESSION

	Any Innovation	Product Innovation	Process Innovation	Marketing Innovation	Organizational Innovation	Social Innovation
R&D Activity	1.313	0.863	0.798	0.412	0.406	0.666
	(0.106)**	(0.081)**	(0.086)**	(0.089)**	(0.080)**	(0.100)**
Innovation Activity	2.397	1.183	2.125	1.062	1.240	0.806
	(0.078)**	(0.071)**	(0.069)**	(0.080)**	(0.069)**	(0.097)**
Source Competitors	-0.403	-0.381	0.216	0.089	-0.111	-0.349
	(0.495)	(0.283)	(0.405)	(0.282)	(0.268)	(0.301)
Source Clients	0.586	0.868	0.296	0.676	0.378	0.296
	(0.120)**	(0.084)**	(0.094)**	(0.090)**	(0.083)**	(0.105)**
Source Government	0.152	0.048	-0.024	0.105	0.151	0.573
	(0.214)	(0.143)	(0.163)	(0.149)	(0.137)	(0.146)**
Highly Educated	0.412	0.439	0.390	0.307	0.383	0.349
	(0.095)**	(0.109)**	(0.092)**	(0.118)**	(0.101)**	(0.147)*
Total Employees	0.062	0.029	0.059	0.010	0.077	0.066
	(0.017)**	(0.019)	(0.016)**	(0.021)	(0.018)**	(0.025)**
Constant	-1.760	-2.097	-1.768	-1.818	-2.244	-2.093
	(0.171)**	(0.197)**	(0.168)**	(0.183)**	(0.195)**	(0.203)**
N	5519	5519	5519	5519	5519	5519

* p<0.05; ** p<0.01

Source: Own calculations based on the Chilean Innovation Survey 2019-2020.

TABLE 5

BINARY TWO-STAGE HECKMAN INSTRUMENTAL VARIABLE REGRESSION

	1st Stage R&D Activity	Any Innovation	Product Innovation	Process Innovation	Marketing Innovation	Organizational Innovation	Social Innovation
Innovation Activity	0.941	0.758	0.212	0.731	0.165	0.279	0.048
	(0.074)**	(0.014)**	(0.013)**	(0.015)**	(0.012)**	(0.014)**	(0.009)**
Source Competitors	0.117	-0.054	-0.084	0.068	0.060	0.016	-0.037
	(0.323)	(0.059)	(0.051)	(0.061)	(0.046)	(0.054)	(0.035)
Source Clients	0.997	0.250	0.271	0.218	0.230	0.129	0.015
	(0.083)**	(0.021)**	(0.019)**	(0.022)**	(0.017)**	(0.020)**	(0.013)
Source Government	0.575	0.143	0.012	0.113	0.044	0.058	0.138
	(0.145)**	(0.031)**	(0.027)	(0.032)**	(0.024)	(0.029)*	(0.019)**
Highly Educated	0.792	0.093	0.040	0.091	0.037	0.043	0.008
	(0.123)**	(0.014)**	(0.012)**	(0.014)**	(0.011)**	(0.013)**	(0.008)
Total Employees	0.203	0.019	-0.000	0.019	0.003	0.010	0.000
	(0.021)**	(0.003)**	(0.002)	(0.003)**	(0.002)	(0.002)**	(0.002)
Exports USD$500.000+	0.348						
	(0.098)**						
Public Inn. Funding	1.080						
	(0.116)**						
R&D Activity		-0.177	0.295	-0.272	-0.041	0.051	0.198
		(0.041)**	(0.039)**	(0.043)**	(0.035)	(0.042)	(0.027)**
Constant	-3.162	0.002	0.019	-0.003	0.044	-0.017	0.052
	(0.239)**	(0.024)	(0.021)	(0.026)	(0.019)*	(0.023)	(0.015)**
	5519	5519	5519	5519	5519	5519	5519
lambda		0.265	0.022	0.277	0.063	0.026	-0.055
		(0.022)**	(0.021)**	(0.023)**	(0.019)**	(0.023)	(0.015)**
Rho		0.962	-0.096	0.962	0.281	0.054	-0.395
Sigma		0.275	0.236	0.287	0.215	0.252	0.165

* p<0.05; ** p<0.01

Source: Own calculations based on the Chilean Innovation Survey 2019-2020.

7. Concluding Remarks

Innovation is widely recognized as a key driver of economic growth and competitiveness. As societies and economies become increasingly complex, firms' ability to adapt and innovate becomes paramount. This study aimed to shed light on the factors that contribute to successful innovation by examining the impact of diverse knowledge sources on different types of innovation outputs. By leveraging reliable innovation survey data from Chilean firms, we have made significant contribution to the understanding of innovation dynamics in emerging economies.

To consolidate our understanding of the role of external knowledge sources in enhancing firms' innovative performance, our study investigates the effects of sourcing knowledge from various external actors. We studied the importance of knowledge from customers, competitors, and public institutions over product, process, marketing, organizational and social innovation outputs.

Several other works have evaluated this relation before in different contexts. The study by Medase and Basit (2019a) studied the impact of different knowledge sources on different types of innovation outcomes among German firms. Previous studies had focused of the relation between information from customers and product innovation (Tsai, 2009 and Vega-Jurado et al., 2009). Much of the previous literature on this topic follows the idea of the absorptive capacity described by Cohen et al., (2002) and focuses on manufacturing firms while this research was able to use data from primary, secondary, and tertiary sectors.

Most of the work in the literature including Ahrweiler (2011), Basit and Medase (2019a, 2019b), has found positive effects of external knowledge on innovation performance. But when considering the impact of external knowledge on innovation performance some care must be exercised. The work by Frickel (2011) shown that external knowledge can also have adverse effects that should be adequately managed by firms for incoming information to benefit innovation performance overall. Under specific circumstances, negative effects of information sources have been mentioned by authors and must be taken into consideration by firm decision makers, especially in the presence of multiple innovation information sources (see Barge-Gil, 2010; Grimpe and Sofka, 2009; Hurmelinna-Laukkanen, 2011).

Our findings underscore the importance of external knowledge sources in driving innovation outcomes. Information sourced from customers emerges as a critical factor, positively influencing most types of innovation. This highlights the significance of customer feedback and the need for firms to adopt customer-centric approaches in their innovation processes. The results align with recent management literature emphasizing the central role of customers in shaping successful business models.

Interestingly, information from competitors demonstrates limited or no impact on innovation output across all types. This challenges the notion that firms can derive substantial benefits from competitor knowledge alone. While this finding may be influenced by endogeneity concerns or a low uptake of competitor information, it suggests that firms should explore alternative knowledge sources beyond their immediate competitors to foster innovation. Recent work by Basit and Medase (2019b) had previously found that knowledge sources from competitors have a significant negative relationship with innovation activities. Our work has shown that this relation is not significant for the case of the Chilean firms. It is therefore reasonable to think that there may be at least no positive impact of sourcing innovation ideas from competitors.

Government information emerges as a valuable resource, particularly for social innovation. It also exhibits positive effects on process and organizational innovations, albeit with smaller magnitudes. These findings underscore the potential role of government agencies in facilitating innovation activities, especially in areas of social importance. Policymakers can leverage these insights to design effective policies that encourage collaboration between firms and government entities, fostering innovation in targeted domains.

While our results indicate that external knowledge from customers and government can foster innovative performance, our results also confirm that R&D, innovation spending, human capital and firm size remain strong determinants of innovation success, as proposed in the literature that follows Crepon, Duguet and Mairesse (1998).

Moreover, our study highlights the significance of other innovative investment beyond traditional R&D. Such investments have emerged as a significant determinant of all types of innovation outputs, emphasizing the need for firms to adopt a holistic approach that encompasses diverse innovation initiatives. This finding suggests that firms can enhance their innovation performance by leveraging various avenues for knowledge acquisition and exploration, beyond R&D investments alone.

The results also indicate that firm size plays a nuanced role in innovation outcomes. While smaller firms can achieve certain types of innovation outputs without clear disadvantages due to their size, the impact of firm size on process and organizational innovations is relatively lower compared to other variables. This implies that innovation success is not always determined by firm size and that smaller firms can effectively compete in specific domains of innovation.

This study investigated the combination of the external sources of knowledge flows, the proportion of graduate employees, innovation expenditure, firm size, and internal R&D to find how these variables impact the likelihood of innovation success measured by five types of different innovation outputs. This paper contributes to the discussion on the significance of external knowledge to the performance of the innovative firms in the context of the Chilean economy. One important novelty of this work was to identify the determinants of social innovation among Chilean firms. This analysis showed that social innovation is affected differently by the same innovation determinant variables. Particularly, we discovered that the most important determinant of social innovation is sourcing innovation ideas from government institutions. We have also considered the endogeneity present on the model and have addressed it with a proven empirical strategy using instruments that are statistically valid. This work was based on the idea that firms are not self-reliant regarding information resources and that they require to add information and ideas from other firms and institutions to better perform on their innovation outcomes.

By providing a comprehensive analysis of the relationships between information sources and innovation outputs, this research contributes to the existing literature and informs strategic decision-making processes in both the public and private sectors. Policymakers can utilize these findings to design targeted policies that foster specific types of innovation, thereby driving local economies forward. Additionally, firms can leverage these insights to develop innovation strategies that capitalize on diverse knowledge sources, empowering them to stay competitive in a rapidly evolving landscape. From the perspective of managers, it is important to decide which origin of knowledge fits best for a particular firm´s objectives. Considering, for example, that public sources increase the likelihood of social innovation while customer sources are related to more product and process innovations.

While this study sheds light on the unique context of Chilean firms. The analysis could also be extended to the comparison of data from different countries across a common period, to learn of differences that could arise between varied economies. Further investigation is also needed to delve deeper into the mechanisms through which diverse knowledge sources influence innovation outcomes. Such research will contribute to a more comprehensive understanding of innovation dynamics and aid in the formulation of evidence-based policies that stimulate innovation-driven growth.

Moreover, we find that more research is needed to discuss to what extent information sources relate to different innovation outputs depending on characteristics of the sector, and some of the firm's internal capabilities. Future research should also try to use databases that include a panel of the same group of firms. In this research we used cross-section data, and our findings are limited the frame of the data set. A panel would also allow to identify longer term effects of the explanatory variables which would certainly be an interesting question to ask.

References

Anzola-Román, P., Bayona-Sáez, C., & García-Marco, T. (2018). "Organizational innovation, internal R&D and externally sourced innovation practices: Effects on technological innovation outcomes." Journal of Business Research, 91, 233-247.

Ahrweiler, P., Pyka, A. and Gilbert, N. (2011), "A new model for university-industry links in knowledge-based economies", Journal of Product Innovation Management, Vol. 28 No. 2, pp. 218-235

Arvanitis, S., Lokshin, B., Mohnen, P., & Wörter, M. (2013)." Impact of external knowledge acquisition strategies on innovation: A comparative study based on Dutch and Swiss panel data." KOF Working Papers No. 325.

Basit, S. A., & Medase, K. (2019a). "The diversity of knowledge sources and its impact on firm-level innovation: Evidence from Germany." European Journal of Innovation Management, 22(4), 681-714.

Basit, A., & Medase, K. (2019b)." The endogeneity of R&D on innovation outputs: Evidence from German SMEs." Research Policy, 48(2), 474-491.

Basit, S. A. (2021). "The effect of external knowledge sources on organizational innovation in small and medium enterprises in Germany." Business Systems Research, 12(1), 60-79.

Bach, M. P., Lojpur, A., Peković, S., & Stanovčić, T. (2015). "The influence of different information sources on innovation performance: Evidence from France, The Netherlands, and Croatia." Southeast European Journal of Economics and Business, 10(2), 89-101.

Barge-Gil, A. (2010), "Cooperation-based innovators and peripheral cooperators: an empirical analysis of their characteristics and behavior", Technovation, Vol. 30 No. 3, pp. 195-206.

Birkinshaw, J., Hamel, G., & Mol, M. J. (2008). "Management innovation." Academy of Management Review, 33(4), 825-845.

Božić, L., & Mohnen, P. (2016). "Determinants of innovation in Croatian SMEs: Comparison of service and manufacturing firms." UNU-MERIT Working Papers, ISSN 1871-9872.

Castellacci, F. (2008)." Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation." Research Policy, 37(6-7), 978-994.

Chang, W., & Taylor, S. A. (2016). "The effectiveness of customer participation in new product development: A meta-analysis." Journal of Marketing, 80(1), 47-64.

Chen, Q., Wang, C. H., & Huang, S. Z. (2019). "Effects of organizational innovation and technological innovation capabilities on firm performance: Evidence from firms in China's Pearl River Delta." Asia Pacific Business Review, 26(1), 1-25.

Choi, S. B., Lee, S. H., & Williams, C. (2011). "Ownership and firm innovation in a transition economy: Evidence from China." Research Policy, 40(3), 441–452.

Cohen, W. M., & Levinthal, D. A. (1990). "Absorptive capacity: A new perspective on learning and innovation." Administrative Science Quarterly, 35(1), 128-152.

Crepon, B., Duguet, E., & Mairesse, J. (1998). "Research, innovation, and productivity: An econometric analysis at the firm level." Economics of Innovation and New Technology, 7(2), 115-158.

Criscuolo, P., Laursen, K., Reichstein, T., Salter, A. (2018). "Winning combinations: search strategies and innovativeness in the UK." Industry and Innovation, 25(2), 115-143.

Damanpour, F., Sanchez-Henriquez, F., Chiu, H. H. (2018). "Internal and external sources and the adoption of innovations in organizations." British Journal of Management, 29(4), 712-730.

Dotzel, K. R., Faggian, A. (2019). "The impact of external knowledge sourcing on innovation outcomes in rural and urban businesses in the US." Growth and Change, 50(2), 515-547.

Gómez, J., Salazar, I., Vargas, P. (2016). "Sources of information as determinants of product and process innovation." PLoS One, 11(4), e0152743.

Geroski, P. A. (1990). "Innovation, Technological Opportunity, and Market Structure." Oxford Economic Papers, 42, 586-602.

Geroski, P. A., Van Reenen, J., & Walters, C. F. (1997). "How persistently do firms innovate?" Research Policy, 26, 33-48.

Grimpe, C. and Sofka, W. (2009), "Search patterns and absorptive capacity: low and high technology sectors in European countries", Research Policy, Vol. 38 No. 3, pp. 495-506.

Harris, R., & Trainor, M. (1995). "Innovations and R&D in Northern Ireland Manufacturing: A Schumpeterian Approach." Regional Studies, 29, 593-604.

Harris, R., & Moffat, J. (2011). "R&D, Innovation and Exporting." SERC Discussion Papers 0073, Centre for Economic Performance, LSE.

Hair, J., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). "Multivariate data analysis" (7th ed.). Pearson Prentice Hall.

Heckman, J. J. (1979). "Sample Selection Bias as a Specification Error." Econometrica, 47(1), 153–161.

Hurmelinna-Laukkanen, P. (2011), "Enabling collaborative innovation – knowledge protection for knowledge sharing", European Journal of

Innovation Management, Vol. 14 No. 3, pp. 303-321.

Kriaa, M., & Karray, Z. (2010). "Innovation and R&D Investment of Tunisian Firms: A Two-Regime Model with Selectivity Correction." The Journal of Business Inquiry, 9(1).

Mairesse, J., & Mohnen, P. (2002). "Accounting for Innovation and Measuring Innovativeness: An Illustrative Framework and an Application." The American Economic Review, 92, 226-230.

Mairesse, J., & Mohnen, P. (2004). "The importance of R&D for innovation: A reassessment using French survey data." Journal of Technology Transfer, 29(1), 41-62.

Mairesse, J., & Mohnen, P. (2010). "Using innovation surveys for econometric analysis." UNU-MERIT working paper #2010-023.

Malerba, F., & Orsenigo, L. (1999). "Technological entry, exit and survival: an empirical analysis of patent data." Research Policy, 28, 643-660.

Mansfield, E. (1969). "Industrial research and technological innovation: an econometric analysis." Published for the Cowles Foundation for Research in Economics at Yale University by Longmans,

OECD/Eurostat (2018). "Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation, 4th Edition, The Measurement of Scientific, Technological and Innovation Activities." OECD Publishing, Paris/Eurostat, Luxembourg. Retrieved from https://doi.org/10.1787/9789264304604-en.

Peters, B. (2009). "Persistence of innovation: stylized facts and panel data evidence." The Journal of Technology Transfer, 34, 226-243.

Piga, C. A., & Vivarelli, M. (2004). "Internal and External R&D: A Sample Selection Approach." Oxford Bulletin of Economics and Statistics, 66(4), 0305-9049.

Mol, M. J., & Birkinshaw, J. (2014). "The role of external involvement in the creation of management innovations." Organization Studies, 35(9), 1287-1312.

Mulgan, Geoff (2007) "Social Innovation: what it is, why it matters and how it can be accelerated". Oxford Said Business School. Printed by The Basingstoke Press ISBN 1-905551-03-7 / 978-1-905551-03-3.

Papke, L. E., & Wooldridge, J. M. (1996). "Econometric methods for fractional response variables with an application to 401(k) plan participation rates." Journal of Applied Econometrics, 11(6), 619-632.

Schumpeter, J. A. (1934). "The theory of economic development." Cambridge, MA: Harvard University Press.

Sofka, W., & Grimpe, C. (2010). "Specialized search and innovation performance – evidence across Europe." R&D Management, 40(3), 310-323.

Teece, D. J. (1986). "Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy." Research Policy, 15(6), 285-305.

Tortia, Ermanno C., Florence Degavre and Simone Poledrini (2020) Why are social enterprises good candidates for social innovation? Looking for personal and institutional drivers of innovation. © 2020 The Authors Annals of Public and Cooperative Economics © 2020 EMF

Tsai, K.H. (2009), "Collaborative networks and product innovation performance: toward a contingency perspective", Research Policy, Vol. 38 No. 5, pp. 765-778.

Vega-Jurado, J., Gutiérrez-Gracia, A. and Fernández-de-Lucio, I. (2009), "Does external knowledge sourcing matter for innovation? Evidence from the Spanish manufacturing industry", Industrial and Corporate Change, Vol. 18 No. 4, pp. 637-670.

Quality managment and labor productivity of formal companies in Perú: A non – experimental design and causal machine learning techniques*

Gestión de calidad y productividad laboral de las empresas en el Perú: Un diseño no experimental y técnicas de machine learning causal.

Mario D. Tello**
Daniel S. Tello Trillo***

Abstract

This paper evaluates the impacts of quality management tools on the labor productivity of companies in Peru for the period 2014-2019 based on causal Machine Learning (ML) techniques (MLC), which reduce or eliminate three potential problems: the endogeneity of the variables of interest, the existence of confusing variables (confounding) and overfitting due to the introduction of many control variables. Using the National Survey of Companies (INEI-ENE 2023), the evaluation indicates that quality control tools affect the productivity of formal companies, particularly large and medium-sized companies.

Key words: *Labor Productivity, Quality Management, Machine Learning.*

JEL Classification: *J24, L15, P42.*

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Resumen

Este trabajo evalúa los impactos de las herramientas de gestión de calidad sobre la productividad laboral de las empresas del Perú para el periodo 2014-2019 basados en técnicas de Machine Learning (ML, en inglés) causal (MLC), las cuales reducen o eliminan tres potenciales problemas: la endogeneidad de las variables de interés, la existencia de variables confusas (confounding) y el sobre ajuste (overfitting) por la introducción de un número grande de variables de control. Usando la Encuesta Nacional de Empresas (INEI-ENE 2023), la evaluación señala que las herramientas de control de calidad inciden en la productividad de las empresas formales, particularmente de las empresas grandes y medianas.

Palabras clave: *Productividad Laboral, Gestión de Calidad, Machine Learning.*

Clasificación JEL: *J24, L15, P42.*

1. Introducción

La literatura internacional de los impactos de las herramientas (prácticas o instrumentos) de gestión de calidad[1] sobre el desempeño de las empresas es amplia y los resultados de los impactos varían por países y métodos sin llegar a tener una conclusión definitiva o clara a nivel de empresas y países.[2] A diferencia de estudios previos, este trabajo analiza los impactos de dichas herramientas sobre el desempeño de las empresas del Perú, específicamente la productividad laboral, para el periodo 2014-2019 basados en técnicas de Aprendizaje Automático (o Machine Learning[3], ML, en inglés) causal

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1 Entre otras, las normas técnicas, estandarización, y acreditación. En este trabajo no se incluyen las prácticas de metrología que se ocupa de las mediciones, las unidades de medida, los equipos utilizados para efectuarlas, y la verificación y calibración periódica.

2 Ver Cuadro 1.

3 El aprendizaje automático es una rama de la *inteligencia artificial* (*AI en sus siglas en inglés*) y la informática que se centra en el uso de datos y algoritmos para imitar la forma en que aprenden los humanos, mejorando gradualmente su precisión. IBM señala a Samuel (1959) como el que acuñó el término "aprendizaje automático". El aprendizaje automático es un componente importante del creciente campo de la ciencia de datos. Mediante el uso de métodos estadísticos, los algoritmos se entrenan para hacer clasificaciones o predicciones, descubriendo información clave dentro de los proyectos de minería de datos (data mining). (https://www.ibm.com/cloud/learn/machine-learning). Por otra parte, AI es una rama de la informática que se ocupa de la construcción de máquinas inteligentes capaces de realizar tareas que normalmente requieren inteligencia humana. En https://builtin.com/artificial-intelligence.

(MLC).[4] La utilización de estas técnicas se debe, por un lado, al hecho de que las empresas escogen o no el uso de prácticas de gestión calidad, lo que implica que dicha selección es endógena y asociada al desempeño de las empresas. Consecuentemente, estimadores de los parámetros de las variables de interés (i.e., las prácticas de gestión de calidad) que no consideran dicha endogeneidad serían sesgados. Por otro lado, la productividad laboral puede estar asociada a innumerables factores los cuales si no son tomados en cuenta en una determinada especificación pueden también sesgar los estimadores de los parámetros de interés. Asociado a este problema está el número adecuado de variables de control que inciden en la productividad laboral que puede producir errores de sobreajuste o overfitting.[5] Estos problemas de endogeneidad de selección de las prácticas de la gestión de calidad y el adecuado manejo de las denominadas 'confounding variables' insertadas como variables de control que afectan el desempeño económico de las empresas, son reducidos o potencialmente eliminados usando técnicas de 'Machine Learning' causal (MLC).[6]

El trabajo se compone de seis secciones aparte de la introducción. La Sección 2 describe el marco conceptual de la relación entre las herramientas de calidad y la productividad de las empresas. La Sección 3 resume la literatura del tema del trabajo. La Sección 4 describe la base de datos usada y presenta un análisis breve de los datos a emplearse para la aplicación de la metodología. La Sección 5 presenta una síntesis de la metodología de evaluación. La Sección 6 muestra los resultados de las estimaciones. La Sección 7 resume las conclusiones del estudio. Al final se lista las referencias.[7]

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4 Término definido por Baiardi & Naghi (2020).

5 En términos simples, el problema de 'overfitting' o sobreajuste de un modelo es una condición en la que un modelo estadístico comienza a describir el error aleatorio en los datos en lugar de las relaciones entre las variables. Este problema ocurre cuando el modelo es demasiado complejo. En el análisis de regresión, el sobreajuste puede producir valores de R-cuadrado, coeficientes de regresión y p-values engañosos.

6 De acuerdo con Baiardi & Naghi (2020), estas técnicas i) son herramientas de uso de datos para recuperar interacciones complejas entre variables y estimar exiblemente la relación entre el resultado, el indicador de tratamiento y las covariables; ii) permiten incluir un gran número de covariables, aún cuando el tamaño de la muestra es pequeña, y el uso de regresiones regularizadas; iii) permite implementar una selección del modelo sistemáticamente; y iv) resultan muy útiles cuando el interés es en estimar los efectos de tratamientos heterogéneos.

7 También está disponible para los lectores un anexo de cuadros que complementa el traa bajo.

2. Marco Conceptual de los Estándar de Calidad y Productividad

Existen diversas teorías que relacionan los estándares de calidad[8] y la productividad de las empresas[9]. Lakhe & Mohanty (1994) presenta una esquema consistente con la teoría de la gestión de calidad total (TQM)[10] que relaciona los sistemas de calidad con la productividad de las empresas. La Figura 1 resume dicho esquema donde los tres principales insumos de la gestión de calidad total son: el compromiso de los agentes (gerencia) de la gestión de calidad, el trabajo en equipo y la participación de los gerentes en la gestión de calidad y los sistemas de calidad. De acuerdo con Zhanga, Song, & Song (2014), los estándares de calidad son parte del sistema de calidad. Los insumos TQM conllevan a generar mecanismos o resultados intermedios que en última instancia inciden en los dos objetivos centrales de la TQM, los beneficios económicos y la productividad de las empresas. Entre los mecanismos que pueden lograr estos objetivos figuran mejora en los servicios y productos de calidad, la satisfacción y lealdad de los clientes, y el logro de un incremento y/o sostenibilidad en la participación de la empresa en el mercado.

Dos elementos cruciales dentro del llamado ‘plan de calidad’ en los diferentes enfoques de la teoría TQM son las ventas y la reducción de costos (Mauch 2010, y Zhang 2000 y 1997). Ante la falta de información para estimar la productividad laboral (ratio de valor real de producción por trabajador) y la productividad total factorial (factor que incide en la función de producción), el ratio ventas reales por trabajador resulta una adecuada proxi de la productividad laboral de las empresas para los enfoques TQM. Así, incrementos de las ventas debido a los mecanismos TQM, y manteniendo lo demás constante, incrementa la productividad laboral de las empresas basada en ventas. De la misma manera, la reducción de costos, inducido por tecnologías que ahorran el uso de la mano de obra, pueden también incrementar la productividad laboral medido en ventas reales por trabajador. Por otro lado, si bien los estándares de

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8 Estos son acuerdos documentados que contienen especificaciones técnicas u otros cri-terios precisos para ser utilizados consistentemente como reglas, lineamientos o definiciones, para asegurar que los materiales, productos, procesos y servicios sean aptos para su propósito. Los estándares incluyen estándares ambientales; estándares orgánicos; normas laborales; normas sociales; y estándares normativos (FAO, 2003).

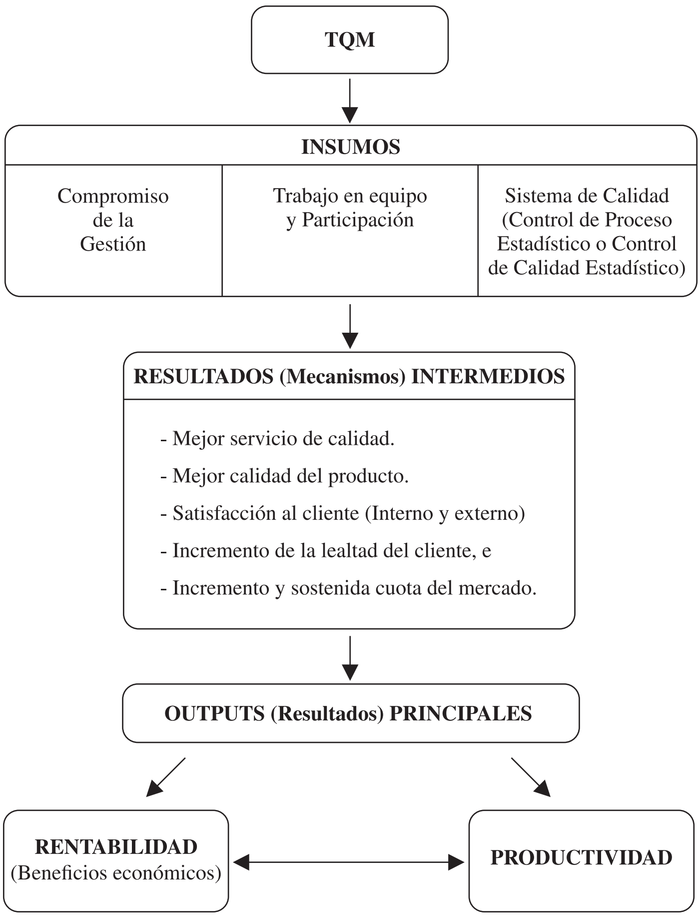
9 Una simple búsqueda en GPT3.5 indica al menos 7 teorías (o marco conceptuales): i) la teoría de gestión de calidad total (Total Quality Management, en inglés); ii) la teoría del conocimiento profundo de Deming (1993); iii) ISO 9000 y el cumplimiento de normas; iv) seis sigma; v) Marco de Excelencia Baldrige; vi) teoría de la contingencia; y vii) la teoría de la calidad como un recurso.

10 Detalles de la TQM en Dotchin & Oakland (1992), Lakhe & Mohanty (1994), Koskela, Tezel, Patel (2019). Zhang (2000). De acuerdo con Zhang (2000, 1997) los pioneros que desarrollaron la TQM son: Deming; Crosby; Juran; Ishikawa y Feigenbaum.

calidad (FAO 2003) y los sistemas de calidad son diversos[11], sus efectos sobre la productividad laboral de las firmas pueden ser estimados bajo el enfoque empírico del presente estudio en concordancia con la literatura empírica descrita en la siguiente sección.

FIGURA 1

TQM Y LA PRODUCTIVIDAD EN EMPRESAS



Fuente: Lakhe & Mohanty (1994). Elaboración propia.

11 https://www.tuv-nord.com.mx/2020/03/04/quality-management-system-que-es-y-para-que-sirve/

Un factor adicional que pueden incidir en el enfoque TQM es el papel de las empresas multinacionales. De acuerdo con Tetteh &. Uzochukwu (2015) y Jiménez-Jiménez, Martínez-Costa, Martínez-Lorente, y Ahmed Dine Rabeh (2015) la aplicación de prácticas de gestión de la calidad total en empresas multinacionales mejora el desempeño organizacional para alcanzar los objetivos comerciales en el entorno comercial global. En la metodología propuesta la variable de interés son los instrumentos de la gestión de calidad que recogen los potenciales efectos de empresas multinacionales, aunque no se identifique a éstas. Sin embargo, los efectos de las características propias de las empresas extranjeras no se identifican en el estudio por falta de información de la propiedad de las empresas extranjeras. Finalmente, desde la perspectiva teórica, las otras variables que afectan a la productividad provienen de la literatura de los determinantes de la productividad, en particular de los enfoques propuestos por Svverson (2011). El número de dichas variables son administradas adecuadamente por el método DML propuesto.

3. Revisión de la Literatura Empírica

El Cuadro 1 resume una lista selecta de trabajos relacionada a los objetivos del estudio. Estos trabajos se diferencian por: ámbito geográfico (empresas de países desarrollados y en desarrollo), herramientas de gestión de calidad (por ejemplo, adopción de certificaciones de calidad internacionales, QC; certificación ISO 9001; 9000, y 14001, y certificación de estándares internacionales -ISC); indicador de desempeño de las empresas de distintos tamaños (entre otros, margen extensivo-incorporación de nuevos productos de exportación, e intensivo de exportaciones-cambios del valor de los productos de exportación; productividad laboral; productividad total factorial, PTF; ventas y retornos en activos, ROA), por período de análisis (entre 1995 y 2014); y por tipo de método econométrico usado (entre otros, random forest; panel data; propensity score matching; mínimos cuadrados en dos etapas, método de momentos generalizados, y fronteras estocásticas de producción).

En cuanto a los resultados obtenidos del impacto, los estudios revisados señalan, por un lado, que los impactos del uso de prácticas de gestión de calidad sobre diversos indicadores del desempeño económico de las unidades de análisis son variados y no existe claridad en dichos impactos. Así, un poco más de la mitad de los trabajos no encuentran incidencia estadísticamente significativa de las herramientas de gestión sobre el desempeño de las empresas. De otro lado, los efectos positivos de las herramientas de gestión dependen del tamaño de las empresas, siendo las grandes las que mejor aprovechan las herramientas de gestión de calidad. Esta diversidad o no claridad de los resultados, por lo menos en parte, está relacionada a los métodos de estimación usados. Muchos de ellos adolecen del problema de endogeneidad de la variable de interés (i.e., la selección por parte de la unidad de análisis de usar o no una práctica de gestión de calidad). Más aún, a excepción del estudio de Mena (2020)[12] no existen trabajos que usan las herramientas de Machine Learning Causal para la estimación del impacto de la variable de interés sobre el desempeño de las firmas. La sección siguiente presenta un análisis de la información y los problemas de estimación que origina.

TABLA 1

RESUMEN DE UNA SELECCIÓN DE ARTÍCULOS SOBRE EL IMPACTO DE LAS PRÁCTICAS DE GESTIÓN DE CALIDAD

No	Autores (año)	Descripción	Resultados
1	Gallardo y Guitierrez (2021)	El estudio estima el impacto de las certificaciones de calidad ISO9001 en el desempeño de la empresa y en las habilidades humanas como mediador en relación del desempeño y la certificación de las empresas en Colombia. El desempeño de las empresas se mide mediante la innovación, productividad laboral, ventas y salarios En el estudio se implementa un modelo de Diferencias en Diferencias y un Propensity Score Matching con efectos fijos. La base de datos consta de un panel de empresas certificadas y empresas no certificadas obtenido de la Encuesta de Desarrollo e Innovación Tecnológica (EDIT) y la Encuesta Anual Manufacturera (EAM) para el periodo 2005-2010.	Se encuentra que el desempeño de las empresas con certificación ISO9001 (de Colombia en el periodo analizado) mejora en contraste con las empresas sin certificación. Más específicamente, en las empresas con certificación la innovación incrementa en 5,2%, la productividad laboral en 4,6%, las ventas en 5,7% y salarios en 4,9%. Asimismo, se encuentra que las empresas certificadas con un mayor porcentaje de trabajadores temporales se desempeñan por debajo de empresas certificadas con fuerza laboral estable y permanente.

[12] La técnica de Random Forest, Mena (2020) lo utiliza para determinar la probabilidad de que una empresa use una práctica de gestión de calidad.

No	Autores (año)	Descripción	Resultados
2	Mena (2020)	El estudio evalúa el impacto de la adopción de certificaciones de calidad internacionales (QC) en el desempeño de las empresas. Utilizando un panel de 4.668 empresas de América Latina y el Caribe. Las bases usadas son: i) la Encuesta de Empresas del Banco Mundial (WBES), años 2006 y 2010 (las de Brasil son de los años 2003 y 2009), ii) Latin American Country Enterprise Survey (LACE) realizada en 2011 en combinación con la nueva ronda realizada en 2014 (PROTEqIN) para los países del Caribe. El trabajo realiza dos tipos de estimaciones: i) mediante el algoritmo Random Forest, se estima la probabilidad de que una empresa adopte QC; y (ii) Con las probabilidades estimadas se estima el impacto del QC sobre los márgenes intensivo y extensivo de las exportaciones de las empresas; el acceso al financiamiento, ventas locales y la productividad mediante diferencias en diferencias ponderadas.	Los resultados de trabajo indican que adquirir una QC tiene un efecto positivo en el comportamiento exportador de las empresas impulsado por un aumento en el margen tanto intensivo como extensivo de las exportaciones indirectas. Las QC también ayudan a disminuir las restricciones en el acceso a la financiación, pero no se encontró ningún efecto sobre las ventas locales y varias medidas de la productividad de la empresa. Sin embargo, los estimados revelan que los impactos positivos de las QC dependen del tamaño de la empresa: solo se benefician las empresas pequeñas y medianas.
3	Bernini, Garone, Maffioli y Mena (2019)	El estudio estima el impacto de la certificación de calidad sobre el desempeño de las firmas, medido por las exportaciones, las ventas locales, la productividad (PTF y productividad laboral) y el acceso al crédito de 5410 empresas de América Latina y el Caribe en el periodo 2006-2010. Se estima, en primera instancia, la probabilidad de las que las empresas tengas un certificado de calidad mediante técnica de Random Forest y luego se emplea el enfoque de diferencias en diferencias para estimar el efecto de la certificación sobre el desempeño de las firmas. Para ello utiliza la World Bank Enterprise Survey y PROTEqIN.	Se encuentra que la certificación de calidad incrementa significativamente las exportaciones, comercio intensivo y extensivo. Las ventas se ven influenciadas de manera débil pero positiva. Así mismo, reduce la precepción de las firmas del acceso a crédito como una barrera para su crecimiento. En el caso específico de la productividad, no se encuentra resultados de influencia significativa en PTF ni en la productividad laboral.

No	Autores (año)	Descripción	Resultados
4	Gallego y Gutiérrez (2017)	El trabajo estima el impacto de la certificación ISO 9001 en la productividad laboral, medido de las empresas de la industria de la manifactura en Colombia en el periodo 2003-2010. Para ello se implementa primero el Propensity Score Matching para determinar el grupo de control adecuado, posteriormente la estimación del impacto se hace mediante Diferencias en Diferencias con efectos fijos para datos panel de empresas certificadas y empresas no certificadas. La base de datos panel fue construida con Encuesta de Desarrollo e Innovación Tecnológica (EDIT) y la Encuesta Anual Manufacturera (EAM), obteniendo información de 41579 empresas, 6125 empresas con certificación ISO 9001 y 35454 sin dicha certificación.	Se encuentra que las empresas con certificación ISO 9001 incrementan significativamente más su valor agregado por empleado, sus ventas por empleado y el promedio de salarios, que las empresas similares que no se encuentran certificadas. Estos resultados indican que las empresas con certificación ISO 9001 tienen mayor productividad laboral, que las empresas que no cuentan con la certificación.
5	Bernini, Garone y Maffioli (2017)	El trabajo presenta evidencia empírica sobre los determinantes de la adopción de certificaciones internacionales de calidad (ISO) y sus efectos sobre el desempeño de las empresas *argentinas* en los años 2006 y 2010. Los autores sugieren que entre los principales factores que pueden afectar la adopción de las certificaciones figuran las empresas que exportan o son extranjeras, la productividad laboral, la experiencia del gerente, la antigüedad de la empresa, el tamaño de la empresa y el acceso al financiamiento. Los métodos econométricos usados son probit y MCO y por robustez estimaciones de diferencias en diferencias con efectos fijos por sector y provincia y diferencias en diferencias combinado con la técnica de emparejamiento estadístico (propensity score matching o PSM) para comparar grupos de empresas que tienen características similares en el año 2006.	Los resultados indican que las firmas exportadoras, extranjeras y de mayor tamaño (en empleados) presentan mayor nivel de adopción, mientras que aquellas empresas que tienen problemas de acceso al financiamiento tienen una adopción menor. Por otro lado, la obtención de certificaciones tiene un efecto positivo en la probabilidad de exportar y el monto exportado, y, además, genera una reducción en la restricción al crédito de las empresas. Sin embargo, no se encuentra ningún efecto sobre ventas locales ni sobre distintas medidas de productividad de las firmas.

No	Autores (año)	Descripción	Resultados
6	Castro-Silva y Rodriguez (2017)	El trabajo se enfoca en determinar la incidencia de la implementación de la certificación ISO 9001 en el Boyacá en Colombia. Para ello, se consideró, para una encuesta sobre su desempeño, a empresas que contaban con dicha certificación por un mínimo de 2 años. Realiza un análisis exploratorio, descriptivo y cuantitativo, utilizando test.	La implementación del ISO 9001 ha tenido impacto positivo en las finanzas, el comercio y las operaciones de las empresas encuestadas. Este impacto es mayor en tanto más grandes son las empresas. No obstante, los resultados indican que no hay dependencia temporal de las mejoras de beneficios en la empresa respecto al año de certificación.
7	Albulescu, Drăghici, Fistiş, and Truşculescu (2016)	El estudio plantea como objetivo principal estimar el impacto de la certificación ISO 9001 en la productividad laboral de los países de la Unión Europea desde el 2000 al 2013. Los datos utilizados son un compilado de la Eurostat, la base de datos de ISO y la base de datos del Banco Mundial. Usa dos métodos de estimación: 2SLS (mínimos cuadrados en dos etapas) y el GMM (método de momentos generalizados).	En ninguno de los métodos implementados, la certificación ISO 9001 tiene influencia significativa sobre la productividad laboral de los países.
8	Vargas (2016)	El estudio estima el impacto de las certificaciones de calidad (QC) en la innovación de capacidades y en los niveles de productividad de la firma. Para ello, implementa el modelo CDM (Crépon, Duguet and Mairesse) y usa los microdatos de la encuesta de innovación de Perú, correspondiente al periodo 2009-2011.	Las firmas que poseen un certificado de manejo de calidad son más productivas que las que no lo tienen. Adicionalmente, aquellas que introdujeron o mejoraron de manera significativa productos o procesos, son 3 veces más productivas. Finalmente, las empresas que solo innovan son 111% más productivas que las que no innovan pasivas. Sin embargo, las firmas que están certificadas e innovan son notablemente mucho más productivas.

No	Autores (año)	Descripción	Resultados
9	Sanchez-Ollero, García-Pozo y Marchante-Lara (2015)	El trabajo tiene como objetivo estimar el impacto de certificaciones de calidad, ISO 9000, ISO 14000, Internal Q y Q-Mark, y de modelos de calidad, MACT model, SICTED model y EFQM model, en la productividad laboral de las empresas del sector hotelero de España. La base corresponde a los datos obtenidos de una encuesta a los gerentes de 232 hoteles de Andalucía. Se usa la función de producción del modelo teórico Cobb-Douglas, la cual es objeto de una regresión lineal.	El análisis descriptivo sugiere que solo los estándares y modelos de calidad, completamente implementados, específicos a la industria hotelera, incrementan la productividad. El análisis econométrico apoya esto, siendo la certificación Q-Mark, la única significativa. Esta certificación incrementa la productividad laboral en un promedio de 23,27%.
10	Islam, Karim y Habes (2015)	El estudio estima el impacto de la certificación de calidad, ISO 9001, sobre el desempeño financiero y no financiero de las organizaciones. Se implementa una regresión jerárquica y los datos usados son los disponibles dadas las respuestas, 201, obtenidas de una encuesta diseñada por los autores en Malasia.	No se encuentra relación significativa directa entre la certificación ISO 9001 y el desempeño financiero, como la reducción de costos, ROA, crecimiento de ventas. Mientras que la relación es fuerte respecto al desempeño no financiero, indicadores de manejo de recursos humanos, operaciones de calidad, etc. Sin embargo, se encuentra, también, que la certificación definitivamente mejora el desempeño financiero de las empresas, pero lo hace de manera indirecta mediante los beneficios no financieros.
11	Fatima (2014)	El trabajo analiza el impacto en el desempeño financiero, medido por beneficio bruto, beneficios netos antes y después de impuestos, de la certificación ISO 9000 en las empresas de Pakistan antes y después de 1995. La base de datos proviene de una encuesta autocompletada de 95 empresas. Para probar la presencia de una relación significativa, o no, entre el desempeño financiero de las empresas y la certificación ISO 9000 se emplea un t-test y el Wilcoxon signed-rank test (WSR test).	Se encuentra que hay una relación significativa entre la certificación ISO 9000 y el desempeño financiero, en cuanto a ventas, beneficio bruto, beneficios netos antes y después de impuestos, para las empresas medianas y grandes. No obstante, no se encuentra relación significativa entre la certificación ISO 9000 y el desempeño financiero en las empresas pequeñas.

No	Autores (año)	Descripción	Resultados
12	Goedhuys & Sleuwaegen (2013)	El estudio examina los efectos de la certificación de estándares internacionales (ISC) en la productividad y las ventas de empresas de un conjunto de países de diferentes grados de desarrollo institucional.	Basado en una muestra de 59 *países* y técnicas de IV (2STLS), los autores encuentran que la ISC aumenta la productividad y el rendimiento de las ventas de las empresas a través de ganancias de eficiencia y señalización de calidad. Los efectos son mayores en países donde las instituciones de apoyo al mercado son débiles. Usa como instrumentos la existencia de licencias y control.
13	Kiplagat (2013)	Se estima el impacto de la certificación ISO 9001:2000 en el desempeño financiero, medido por ROA, crecimiento de ventas y los márgenes de beneficio neto de corporaciones comerciales del estado en Kenia en el periodo 2004-2011. La base de datos se compone por los obtenidos de la Oficina de Normas de Kenia (KEBS), Bureau veritas y de informes anuales de las empresas. El estudio se lleva a cabo mediante la estimación por Mínimos Cuadrados Ordinarios (MCO).	Se encuentra que los tres indicadores financieros, ROA, crecimiento de las ventas y los márgenes de beneficio neto, se ve significativamente influenciados por la certificación ISO 9001. Siendo esto indicador de que esta certificación mejora el desempeño financiero de las corporaciones comerciales del estado.
14	Starke, Eunni, Dias Fouto y de Angelo. (2012)	Se investiga el impacto de la certificación ISO 9000 en ingresos por ventas, costo de los bienes vendidos/ingresos por ventas y el índice de rotación de activos (ventas/activos totales). Para ello se usa datos de panel de empresas que cotizan en bolsa en *Brasil* entre 1995 y 2006. Se estimaron especificaciones con mínimos cuadrados ordinarios, efectos fijos y efectos aleatorios.	Se encuentra que la certificación ISO 9000 está asociada con un aumento en los ingresos por ventas, una disminución en el costo de los bienes vendidos/ ingresos por ventas y un aumento en los índices de rotación de activos de las empresas certificadas. Los resultados sugieren que las empresas grandes y pequeñas, (independientemente de su estructura de capital, es decir, deuda/capital) se beneficiarán de la adopción de las normas ISO 9000.

No	Autores (año)	Descripción	Resultados
15	Ilkay y Aslam (2011)	Se investiga la diferencia en las prácticas de calidad y el desempeño entre las empresas pequeñas a medianas (SMEs) que tienen certificación ISO 9001 y aquellas empresas que no lo tienen en Turquía. El desempeño de las empresas es medido en base a criterio financieros, de negocios internos, de clientes y de innovación y aprendizaje. Se usa datos obtenidos de una encuesta elaborada por los autores a 225 SMEs, junto con la base de datos de SME Information Network. Se estima las diferencias mediante un análisis de varianza unidireccional.	Se encuentra que hay diferencias entre las empresas certificadas con ISO 9001 y las demás empresas solo en el criterio de finanzas. Sin embargo, en el promedio de criterios de desempeño no se muestra una diferencia significativa. Mientras que los resultados son significativos para la diferencia del promedio de las prácticas de calidad entre empresas con la certificación y las empresas sin certificación.
16	Saizarbitori y Landin (2011)	El trabajo se centra en el análisis empírico de la relación entre la certificación ISO 14001 y el rendimiento financiero, el cual es medido por la rentabilidad económica y el crecimiento de las ventas, en el periodo 1997-2006. Para ello utilizan grupos de empresas de la comunidad autónoma del país vasco como grupo de control, 268 empresas sin certificación, y de tratamiento, 7232 empresas con certificación. La base de datos se compone del Catálogo Industrial Vasco y de Exportadores, el registro de empresas certificadas de Ihobe-Sociedad Pública de Gestión Ambiental del Gobierno Vasco y la base de información económico-financiera. Se implementa una metodología longitudinal que mide los rendimientos de las empresas antes y después de la certificación.	Para ambos indicadores de rentabilidad financiera, la rentabilidad económica y el crecimiento de ventas son mayores en las empresas certificadas. También se encuentra que en los años 2000, 2003 y 2004, las empresas sin certificación pero que iban a obtener su certificado ISO 14001 más adelante, eran en promedio, más rentables que las empresas no certificadas. Empresas que se certificarían en un futuro cercano tenían mayor crecimiento de ventas que las no certificadas. Así, no es posible concluir que la certificación ISO 14001 sea causa de los mejores rendimientos financieros de las empresas.

No	Autores (año)	Descripción	Resultados
17	Bewoor y Pawar (2010)	El estudio se centra en conocer el impacto de la implementación de las QMS (Quality Managment System) /ISO 9001-1400 en la productividad o desempeño de empresas pequeñas y medianas en India. Se hace uso de una encuesta de 220 empresas pequeñas y medianas certificadas ISO9001. El trabajo es de tipo exploratorio y plantea 4 pasos para llevarlo a cabo: i) Identificar las variables explicativas del impacto ii) Diseño del cuestionario de la encuesta iii) Recolección de datos y iv) Análisis de datos. Asimismo, considera variables independientes de cada departamento para la estimación.	El efecto de la implementación de ISO/QMS sobre la productividad de las pequeñas y medianas empresas de India son, principalmente, a nivel marginal. Sin embargo, no es la misma para todos los departamentos.
18	Tzelepis, Tsekouras, Skuras y Dimara (2006).	El trabajo explora los efectos de la norma ISO 9001 en la eficiencia productiva de las empresas. La muestra comprende 1572 empresas de tres industrias manufactureras griegas (alimentos y bebidas, maquinarias, y fabricación de aparatos eléctricos y electrónicos). La metodología parte de una frontera estocástica en el cual la norma ISO 9001 puede ser incluida como: i) un insumo de producción, ii) un factor que afecta la eficiencia técnica de la frontera; iii) en ambos como insumo y factor que afecta la eficiencia técnica, y iv) un factor que no afecta la frontera.	El principal resultado de las regresiones estimadas es que ISO 9001 es un factor de gestión que reduce la ineficiencia productiva.

No	Autores (año)	Descripción	Resultados
19	Heras, Dick, y Casadesús (2002)	Se investiga la *causalidad* de incidencia de la certificación de 800 empresas del periodo 1995-2002 de una región de *España,* a través de una comparación con un grupo de control (no certificadas) de las ventas y rentabilidad reales de 400 empresas certificadas pre y post registro.	Los resultados de la prueba de diferencias de promedios (entre el grupo con certificación y sin certificación) indican que, aunque el rendimiento de empresas certificadas es superior a la de 400 empresas no certificadas, no hay evidencia de desempeño mejorado después del registro en las 400 empresas certificadas estudiadas. El desempeño superior de las empresas certificadas se debe a que las empresas con rendimiento tienen una mayor propensión a buscar el registro ISO 9000.
20	Wayham, Kirche, Khumawala (2002)	El estudio explora la relación entre la certificación ISO 9000 y el desempeño financiero. Se usó un diseño de investigación multivariante de medidas repetidas.	Los resultados indican que la certificación ISO 9000 tiene un impacto muy limitado en el desempeño financiero, medido por el rendimiento de activos, sin embargo, este efecto se disipa rápidamente con el tiempo.
21	Häversjö (2000)	Este trabajo analiza las consecuencias financieras de Registro ISO 9000 para empresas danesas, a través de la comparación de dos grupos de empresas, 731 con registro y 644 sin registro.	Los resultados indican que la tasa de rentabilidad de las empresas en el año anterior al registro, eran un 20 por ciento superior a la de la población de control. Luego de dos años después del registro, la tasa de rendimiento fuel 35 por ciento superior a la de la población control. Sin embargo, parece que el efecto positivo es no debido a la mejora de la capacidad interna utilización, sino más bien a un aumento de las ventas.
22	Terziovski, Samson, y Dow (1997)	El propósito del estudio es probar la fuerza de la relación entre la certificación ISO 9000 y el desempeño organizacional en la presencia y ausencia de un entorno de gestión de calidad total (TQM). El análisis usa una gran muestra aleatoria de empresas manufactureras en Australia y Nueva Zelanda.	El hallazgo central es que no se muestra que la certificación ISO 9000 tiene un efecto significativamente positivo en el desempeño de la organización en presencia o ausencia de un entorno TQM. Este apoya la opinión de que, en promedio, la certificación ISO 9000 tiene poco o ningún poder explicativo del desempeño organizacional.

Fuente: Elaboración propia.

4. Análisis de los Microdatos del Modelo

Las variables de estudio son obtenidas de la Encuesta Nacional de Empresas del INEI-ENE (2023) para el período 2014-2019[13]. Se usa dos bases conjuntas o 'pool' de datos de empresas para todos los años (sin distinción de ellos) para los periodos 2014-2017 y 2014-2019. Se usan estas dos bases por robustez estadística y por el hecho que ambas bases contienen distintos números de herramientas de gestión, el periodo 2014-2017 tres herramientas (normas técnicas, certificación y estandarización), y el periodo 2014-2019 dos herramientas (normas técnicas, certificación).

Luego de un proceso de identificación y limpieza de la información[14], las bases seleccionadas registran 1855 observaciones (empresas y años) y 464 empresas en promedio por año en el primer período. En el segundo periodo se registra 3107 observaciones y 621 empresas en promedio por año. Estas muestras de empresas se computan con la base de datos 'limpias' determinadas por la variable binaria de interés $DCAL$ que caracteriza a las empresas que disponen de por lo menos una herramienta de calidad durante el periodo de la muestra.

Los principales estadísticos descriptivos de las dos bases se detallan en el Cuadro 2. El cuadro para base de datos tiene dos columnas: en la primera ($D_{CAL}=1$) se muestra las empresas que disponían por lo menos una herramienta de gestión de calidad, entre normas técnicas, certificaciones (para la estandarización y sistematización de cualquiera de los procesos de compras, producción, almacenamiento, comercialización, transporte y distribución, o servicio postventa) y estandarización[15] en un determinado año; en la segunda ($D_{CAL}=0$), las empresas no disponen de dicha herramienta en cualquiera de los años del período 2014-2019.

También el Cuadro 2 registra 45 variables que potencialmente pueden incidir en la productividad laboral de las empresas.[16] Dentro de las 45 variables

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13 El trabajo usa dos encuestas, una para el período 2014-2017 que corresponde al periodo real del 2014-2017 aun cuando el periodo de publicación de las encuestas es del 2015-2018; la otra para el periodo 2014-2019 que también corresponde al mismo período en términos reales. La encuesta del 2019 fue publicada el 2020 aunque los datos reales corresponden al año 2019.

14 Detalles en el anexo disponibles al lector, Cuadros A1 y A2.

15 Las dos primeras herramientas para el periodo 2014-2019 y las tres herramientas para el periodo 2014-2017.

16 Syverson (2011) describe una lista de dichos factores teóricos a través de los efectos soe bre la productividad total factorial. Cabe señalar que teóricamente $PL_{it}=A.F\left(k_{it}\right)$, donde A es la productividad factorial total, k_{it} es el ratio capital-trabajo y PL_{it} es la productividad laboral. Otros factores que se introducen en las regresiones y cuadros son: $DNET=1$ si la empresa contó con servicio de internet; $CINST$, porcentaje de la capacidad instalada utilizó su empresa en el año; $DCAP=1$ si los trabajadores recibieron alguna capacitación; $DCIF=1$ si para el principal producto de la empresa, existe en el mercado competencia informal.

se incluyen cuatro potenciales variables instrumentales.[17] Estas variables se miden de dos formas. En la primera, se usa una variable binaria representando una característica de la empresa y en la segunda una variable real que mide el porcentaje de firmas de un determinado CIIU y año 't' que tienen la característica de la empresa de la variable binaria. Los CIIU se desagregan en cinco sectores: agropecuario y pesca, minería, manufactura, construcción y comercio, y otros servicios. Para las ocho variables que resultan de las dos formas de medición de las cuatro variables instrumentales básicas, el tamaño de la muestra varía y se indica en la fuente del Cuadro 2. Los valores de las variables instrumentales binarias representan el porcentaje de empresas que tienen o no la característica de dicha variable en cada período. Los valores de las variables instrumentales reales por CIIU y año representan el promedio anual del porcentaje de empresas que disponen la característica de su correspondiente variable instrumental binaria.

La cifras del cuadro indican una notoria diferenciación entre empresas que disponen de por lo menos una herramienta de gestión de calidad ($DCAL = 1$)y de aquellas que no disponen de dichas herramientas ($DCAL = 0$) en los dos períodos considerados. Así, las empresas que disponen de herramientas de calidad: son más productivas, y grandes (en el empleo del número de trabajadores), en su mayoría exportan ($DX = 1$), tienen un alto valor del ratio capital-trabajo (k[18]); y trabajan con tecnologías de punta ($DTEC_1 = 1$)[19] y en dos o tres turnos ($DTurn_2 = 1$)[20].

Por otro lado, la composición muestral en términos del tamaño de las empresas, por número de trabajadores[21] del Cuadro 2 también adiciona 4 criterios con base a ventas de las empresas para la definición de tamaño. El primero,-Ventas 1 sigue la definición de empresas de la Ley No 30056 que Facilita la Inversión e Impulsa el Desarrollo Productivo y el Crecimiento Empresarial. De acuerdo con esta ley una microempresa tiene ventas anuales hasta un monto máximo de 150 Unidades Impositivas Tributarias (UIT); la pequeña empresa tiene ventas anuales superiores a 150 UIT y hasta 1700 UIT; la mediana empresa: ventas anuales superiores a 1700 UIT y hasta 2300 UIT[22] y las empresas

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17 Donde *DCAL&DIF=1* si la empresa percibe que los factores relevantes para su posicionamiento en el mercado son calidad y diferenciación del producto o servicio; $DMIL$=1 si el mercado principal de la empresa es el mercado internacional y nacional; $DIMB$=1 si la actividad de empresa se desarrollada en un espacio exclusivo o independiente; $DOCDG$ =1 si el tipo de registro que utiliza para las órdenes de compra o pedidos son digitales.

18 En las regresiones se introduce como lnk.

19 Donde $DTurn_1 = 1$ la empresa usa tecnología manual.

20 Donde $DTurn_1 = 1$ significa que la empresa trabaja 1 solo turno.

21 De acuerdo con el tamaño en número de trabajadores, las empresas grandes tienen de 100 a más trabajadores (L≥100); las medianas entre 21 y 99 trabajadores (21≤L ≤99; y las pequeñas menos de 21 trabajadores (L<21).

22 En promedio para el periodo 2014-2019, una UIT corresponde a US$ 1.246.

grandes tiene ventas anuales superiores a 2300UIT. Así, en Ventas 1, las micro y pequeñas empresas son agrupadas como 'pequeñas' empresas. En el segundo, Ventas 2, las medianas empresas agrupan a las pequeñas y medianas de empresas según el valor de ventas en UIT. En Ventas 3 se toma como criterio tanto el tamaño en número de trabajadores como el valor de ventas en UIT. Bajo Ventas 2 las pequeñas empresas son las micro y pequeñas según ventas y que tengan menos de 21 trabajadores. El cuarto, Ventas 4, que también toma el número de trabajadores y ventas, la pequeña empresa se define como empresas con menos de 21 trabajadores y las microempresas en ventas. Para todos los criterios de tamaño de empresas las de tamaño grande dominan relativamente la muestra en ambos periodos. Por último, en los dos períodos dominan relativamente las empresas manufactureras.

TABLA 2

PRODUCTIVIDAD LABORAL, INDICADORES DE GESTIÓN DE CALIDAD Y OTROS FACTORES BASE DE DATOS POOL, 2014 -2017 Y 2014 - 2019

No	Variables	Periodo 2014-2017 $NT = 1855$; $\bar{N} = 464$		Periodo 2014-2019 $NT = 3107$; $\bar{N} = 621$	
		$D_{CAL} = 1$ $NT = 1239$; $\bar{N} = 310$	$D_{CAL} = 0$ $NT = 616$; $\bar{N} = 154$	$D_{CAL} = 1$ $NT = 1557$; $\bar{N} = 311$	$D_{CAL} = 0$ $NT = 1550$; $\bar{N} = 310$
1	PL (US dólar 2011 por trabajador)	92877.27	49300.07	101626.83	64875.77
2	$DCAL(\%)$	66.79	33.21	50.11	49.89
3	L	494.93	123.06	523.19	145.38
4	$DLargefirm(\%)$	57.22	10.03	31.35	14.55
5	$DMediumfirm(\%)$	0.22	0.22	12.58	14.97
6	$DSmallfirm(\%)$	7.14	25.18	6.18	20.37
7	$DLargefirm(\%)$ (Ventas 1)	53.58	11.11	37.27	21.95
8	$DMediumfirm(\%)$ (Ventas 1)	3.50	1.24	2.74	3.28
9	$DSmallfirm(\%)$ (Ventas 1)	9.70	20.86	10.11	24.65
10	$DLargefirm(\%)$ (Ventas 2)	54.12	10.57	37.62	21.60
11	$DMediumfirm(\%)$ (Ventas 2)	8.46	6.52	9.24	13.45
12	$DSmallfirm(\%)$ (Ventas 2)	4.20	16.12	3.25	14.84
13	$DLargefirm(\%)$ (Ventas 3)	55.32	9.57	41.89	18.29
14	$DMediumfirm(\%)$ (Ventas 3)	2.55	0.93	2.54	2.82

No	Variables	Periodo 2014-2017 $NT = 1855$; $\bar{N} = 464$		Periodo 2014-2019 $NT = 3107$; $\bar{N} = 621$	
		$D_{CAL} = 1$ $NT = 1239$; $\bar{N} = 310$	$D_{CAL} = 0$ $NT = 616$; $\bar{N} = 154$	$D_{CAL} = 1$ $NT = 1557$; $\bar{N} = 311$	$D_{CAL} = 0$ $NT = 1550$; $\bar{N} = 310$
15	$DSmallfirm(\%)$ (Ventas 3)	5.40	26.23	7.15	27.32
16	$DLargefirm(\%)$ (Ventas 4)	55.29	9.09	42.80	18.52
17	$DMediumfirm(\%)$ (Ventas 4)	6.86	3.35	7.02	8.84
18	$DSmallfirm(\%)$ (Ventas 4)	4.10	21.31	3.37	19.46
19	k (US dólar 2011 por trabajador)	29422.18	10253.21	64647.87	27308.02
20	$DTEC_1(\%)$	37.74	13.75	26.36	19.44
21	$DTEC_2(\%)$	29.06	19.46	23.75	30.45
22	$DNET(\%)$	67.26	32.74	50.34	49.66
23	$DFIN(\%)$	67.39	32.61	50.48	49.52
24	$DTurn_1(\%)$	29.22	23.23	22.37	33.89
25	$DTurn_2(\%)$	37.57	9.97	27.74	16.00
26	$CINST$	74.43	69.79	72.81	69.00
27	$DCAP(\%)$	77.05	22.95	59.59	40.41
28	$DX(\%)$	85.23	14.77	69.34	30.66
29	$DCIF(\%)$	62.00	38.00	46.41	53.59
30	$DCAL\ \&\ DIF(\%)$	79.37	20.63	56.40	43.60
31	$DCAL\ \&\ DIFCIIU_{agri\&pesca}(\%)$	1.42	0.14	1.54	1.57

No	Variables	Periodo 2014-2017 $NT = 1855$; $\bar{N} = 464$		Periodo 2014-2019 $NT = 3107$; $\bar{N} = 621$	
		$D_{CAL} = 1$ $NT = 1239$; $\bar{N} = 310$	$D_{CAL} = 0$ $NT = 616$; $\bar{N} = 154$	$D_{CAL} = 1$ $NT = 1557$; $\bar{N} = 311$	$D_{CAL} = 0$ $NT = 1550$; $\bar{N} = 310$
32	$DCAL \& DIFCIIU_{mineria}(\%)$	0.28	0.00	0.52	0.36
33	$DCAL \& DIFCIIU_{manufact.}(\%)$	66.43	17.35	43.66	51.88
34	$DCAL \& DIFCIIU_{const\&com.}(\%)$	9.10	2.13	11.61	10.38
35	$DCAL \& DIFCIIU_{otros\_serv}(\%)$	2.13	1.00	2.61	2.38
36	$DCAL \& DIFCIIU_{\_total}(\%)$	71.22	28.78	58.72	41.28
37	$DMIL(\%)$ [2]	65.83	34.17	49.24	50.76
38	$DMIL \& CIIU_{agri\&pesca}(\%)$ [2]	1.44	1.43	1.99	1.53
39	$DMIL \& CIIU_{mineria}(\%)$ [2]	0.65	0.00	0.56	0.54
40	$DMIL \& CIIU_{manufact.}(\%)$ [2]	44.82	47.68	43.99	45.90
41	$DMIL \& CIIU_{const\&com.}(\%)$ [2]	10.81	7.99	13.98	13.51
42	$DMIL \& CIIU_{otros\_serv}(\%)$ [2]	1.92	2.23	3.09	3.10
43	$DMIL \& CIIU_{\_total}(\%)$ [2]	1.44	1.43	57.21	42.79
44	$DIMB(\%)$ [3]	67.63	32.37	48.89	51.11
45	$DIMB \& CIIU_{agri\&pesca}(\%)$ [3]	2.97	2.97	2.15	2.03
46	$DIMB \& CIIU_{mineria}(\%)$ [3]	0.73	0.00	0.35	0.44
47	$DIMB \& CIIU_{manufact.}(\%)$ [3]	83.92	83.92	67.82	69.43
48	$DIMB \& CIIU_{const\&com.}(\%)$ [3]	14.89	14.89	13.51	13.18

No	Variables	Periodo 2014-2017 $NT = 1855$; $\bar{N} = 464$		Periodo 2014-2019 $NT = 3107$; $\bar{N} = 621$	
		$D_{CAL} = 1$ $NT = 1239$; $\bar{N} = 310$	$D_{CAL} = 0$ $NT = 616$; $\bar{N} = 154$	$D_{CAL} = 1$ $NT = 1557$; $\bar{N} = 311$	$D_{CAL} = 0$ $NT = 1550$; $\bar{N} = 310$
49	$DIMB \,\&\, CIIU_{otros\_serv}(\%)$ [3]	6.93	6.93	3.62	3.63
50	$DIMB \,\&\, CIIU_{\_total}(\%)$ [3]	63.83	36.17	45.10	54.90
51	$DOCD(\%)$ [4]	76.76	23.24	55.57	44.43
52	$DOCD \,\&\, CIIU_{agri\&pesca}(\%)$ [4]	1.79	1.78	2.14	1.80
53	$DOCD \,\&\, CIIU_{mineria}(\%)$ [4]	0.65	0.00	0.56	0.54
54	$DOCD \,\&\, CIIU_{manufact.}(\%)$ [4]	67.70	51.01	65.96	55.81
55	$DOCD \,\&\, CIIU_{const\&com.}(\%)$ [4]	16.79	13.95	21.37	17.56
56	$DOCD \,\&\, CIIU_{otros\_serv}(\%)$ [4]	3.60	2.59	4.76	4.20
57	$DOCD \,\&\, CIIU_{\_total}(\%)$ [4]	70.57	29.43	56.61	43.39

Fuente: INEI-ENE (2023). Elaboración propia. Los coeficientes de correlación entre PL y D_{CAL} de los datos pool es 0.1611*** (2014-2017) y 0.1425*** (periodo 2014-2019). Los coeficientes de correlación entre PL y $D_{CAL\&DIF}$ de los datos pool es 0.0340 (2014-2017) y 0.0397* (periodo 2014-2019). Los coeficientes de correlación entre PL y $D_{CAL\&DIFCIIU}$ de los datos pool es -0.0431 (2014-2017) y -0.0498** (periodo 2014-2019). Los coeficientes de correlación entre PL y D_{MIL} de los datos pool es 0.0371 (2014-2017) y -0.0518** (periodo 2014-2019). Los coeficientes de correlación entre PL y $D_{MIL\&CIIU}$ de los datos pool es -0.0159 (2014-2017) y -0.0288 (periodo 2014-2019). Los coeficientes de correlación entre PL y D_{IMB} de los datos pool es 0.0513** (2014-2017) y 0.0573*** (periodo 2014-2019). Los coeficientes de correlación entre PL y $D_{DIMB\&CIIU}$ de los datos pool es 0.0309 (2014-2017) y 0.0351(periodo 2014-2019). Los coeficientes de correlación entre PL y D_{DOCD} de los datos pool es 0.1691*** (2014-2017) y 0.1452*** (periodo 2014-2019). Los coeficientes de correlación entre PL y $D_{DOCD\&CIIU}$ de los datos pool es 0.1244*** (2014-2017) y 0.1097*** (periodo 2014-2019). 2 La muestra para estas variables es 1855 para el periodo 2014-2017 y la muestra es de 2048 para el periodo de 2014-2019. 3 La muestra para estas variables es 1855 para el periodo 2014-2017 y la muestra es de 2048 para el periodo de 2014-2019. 4 La muestra para estas variables es 1855 para el periodo 2014-2017 y la muestra es de 2041 para el periodo de 2014-2019. 5 La muestra para estas variables es 1855 para el periodo 2014-2017 y la muestra es de 2048 para el periodo de 2014-2019. Significancia al 1 % (***). al 5 % (**) y al 10 % (*).

TABLA 3

DECILES DE PRODUCTIVIDAD LABORAL POR VARIABLE DE INTERÉS E INSTRUMENTOS: POOL 2014 - 2017

Decil	Rango-PL	$\overline{PL}$	$DCAL_{it}$ (%)	$DCALDIF_{it}$ [1]	$DCAL$ & $DIFCIIU_{.it}$ [1]	$DMIL_{it}$ [2]	$DMIL$ & $CIIU_{it}$ [2]	$DIMB_{it}$ [3]	$DIMB$ & $CIIU_{.it}$ [3]	$DOCDg_{i4t}$ [4]	$DOCD$ & $CIIU_{.it}$ [4]
1	0.00-60151.44	28287.77	5.65	6.26	36.37	9.27	32.67	9.32	50.54	6.71	37.18
2	6020.08-12553.34	9263.37	6.13	6.12	39.67	7.81	35.79	9.92	56.33	6.45	44.19
3	12701.03-20922.24	16811.41	8.15	9.10	39.51	8.61	37.27	10.04	57.41	8.29	46.02
4	20928.67-30911.45	25562.51	10.41	10.38	41.69	9.27	38.48	9.74	59.18	10.53	50.68
5	30919.37-42476.28	36077.21	10.01	12.80	43.00	9.93	40.75	10.16	65.81	10.99	54.14
6	42501.11-55594.67	48387.62	11.78	11.10	40.17	11.13	39.66	10.04	59.62	11.06	55.19
7	55620.78-76037.01	65308.82	11.22	11.81	37.70	11.92	37.55	10.34	60.56	11.19	50.43
6	76038.55-109188.3	92506.03	11.70	11.24	41.34	10.46	41.48	9.98	66.30	11.85	57.17
9	109323.8-186415.6	139011.40	11.62	10.10	46.37	11.13	41.67	10.10	67.79	11.32	56.74
10	187146.5-2144163	349019.90	13.32	11.10	45.69	10.46	41.47	10.34	67.74	11.59	55.22

Fuente: INEI-ENE (2023). Elaboración propia. 1 La muestra para estas variables es 1855. 2 La muestra para estas variables es 1855. 3 La muestra para estas variables es 1756. 4 La muestra para estas variables es 1855.

TABLA 4

DECILES DE PRODUCTIVIDAD LABORAL POR VARIABLE DE INTERÉS E INSTRUMENTOS: POOL 2014 - 2019

Decil	Rango-PL	$\overline{PL}$	$DCAL_{it}$ (%)	$DCALDIF_{it1}$	$DCAL$ & $DIFCIIU_{.it1}$	$DMIL_{it\,2}$	$DMIL$ & $CIIU_{it\,2}$	$DIMB_{it\,3}$	$DIMB$ & $CIIU_{.it3}$	$DOCDg_{i4t\,4}$	$DOCD$ & $CIIU_{.it\,4}$
1	0.00-6799.73	2974.91	6.55	6.64	36.66	9.07	32.37	9.46	43.23	6.95	42.96
2	6847.27-14956.82	10851.90	7.06	5.92	32.62	8.44	30.60	10.07	46.70	6.66	37.10
3	14966.28-23031.95	19014.98	8.35	9.42	38.03	8.06	37.27	9.68	56.22	8.84	50.97
4	23041.59-32491.46	27807.34	9.83	11.35	39.25	9.32	37.12	9.73	49.32	10.55	53.04
5	32513.95-43580.97	37872.38	10.34	12.44	41.82	9.45	38.03	10.18	52.92	10.78	55.48
6	43598.04-58648.09	50433.69	10.98	10.63	33.64	11.21	33.16	10.01	49.10	10.96	45.14
7	58650.00-78841.8	67739.35	10.34	11.23	35.20	11.96	34.08	10.34	49.05	11.08	47.70
6	78907.3-113119.9	94745.08	11.43	11.59	37.78	9.95	39.63	10.07	64.09	11.79	57.79
9	113230.3-200295	148833.10	11.37	9.66	43.68	11.71	39.92	10.07	65.41	11.14	57.55
10	200374.9-1922246	373358.50	13.74	11.11	41.97	10.83	38.28	10.40	66.25	11.26	56.20

Fuente: INEI-ENE (2023). Elaboración propia. 1 La muestra para estas variables es 2048. 2 La muestra para estas variables es 2048. 3 La muestra para estas variables es 2041. 4 La muestra para estas variables es de 2048.

Los cuadros 3 y 4 evidencian otra característica de la variable de interés ($DCAL$) y las variables instrumentales. En estos cuadros la muestra en los dos períodos se divide en 10 deciles de la productividad laboral donde las primeras dos columnas del cuadro indican los rangos de esta variable y su promedio, respectivamente. En las siguientes columnas se reportan el porcentaje de empresas que pertenecen a cada decil y que satisface las características de las variables de interés y las instrumentales. Las cifras del cuadro señalan para todas estas variables, una tendencia creciente de los porcentajes a medida que se incrementa el rango y promedio del decil de productividad. Así, por ejemplo, para el decil más bajo de productividad, entre el 5.7 y 6.6% de la muestra de empresas del período 2014-2019 disponían de al menos una herramienta de calidad, mientras para el decil más alto entre 13.3 y 13.7% de la muestra de empresas en el mismo periodo disponían de por lo menos una herramienta de calidad. El mismo patrón tienen las demás variables.

Las cifras de estos dos cuadros y las correlaciones entre las variable de interés y la productividad laboral[23] si bien proveen indicios que exista una posible injerencia de las herramientas de gestión de calidad en la productividad de las empresas, también es posible que estas herramientas de gestión se 'confundan' con otras variables y sean a través de estas otras que la injerencia se origine. Los trabajos Tello (2021, 2020, 2017 y 2015) señalan que dos de las factores más importantes en la determinación de la productividad laboral de las empresas en el Perú son la intensidad del uso del capital relativo a la mano de obra y el tamaño (en términos del número de trabajadores) de las empresas. Si estas, al igual que la productividad laboral determinasen a su vez al uso de las herramientas de gestión de calidad entonces estimaciones estándar que asuman que estas herramientas determinen la productividad laboral[24] producirían estimadores sesgados de los coeficientes de estas herramientas. Los sesgos también ocurrirían si tanto la productividad laboral y las herramientas de calidad se afectan simultáneamente. La sección siguiente presenta una metodología que permite abordar el problema tanto de las variables 'confounding' (o de confusión en castellano)[25] como el de la endogeneidad de la variable de interés ($DCAL$), dada las cifras de los Cuadros 3 y 4 y las correlaciones con la productividad.

[23] Detalladas en la fuentes del Cuadro 2.

[24] Como en algunos de los trabajos citados en el Cuadro 1.

[25] Confounding variables o variables confusión son variables que son difícil de medir y que afectan tanto a la supuesta variable de interés (X) y a la variable resultado (Y). Así, si Z es la variable confusa y sí, $Y \leftarrow Z \rightarrow X$, then $X \nrightarrow Y$. La estimación del modelo: $Y = X\beta + \varepsilon$ produciría estimaciones sesgadas de β.

5. Metodología de Evaluación

El punto de partida de la metodología que se implementa en el trabajo es la especificación (1):

$$(1) \qquad PL_{it} = \beta.DCAL_{it} + \vec{X}_{it}'.\overline{\delta} + \varepsilon_{it}\ ;\ i = 1,\ldots N; t = 2014 - 2019$$

Donde para cada empresa 'i' y periodo 't', PL_{it} es el logaritmo neperiano de la productividad laboral, $DCAL_{it}$ es la variable de interés de uso de por lo menos una herramienta de gestión de calidad y $\vec{X}_{it}$ es el vector de variables de control (incluyen potenciales variables confounding). En la sección anterior, se presentó indicios que la variable de interés esté asociada con el error estocástico, ε_{it}, y que no sea exógena por lo cual métodos estándar como mínimos cuadrados ordinarios, MCO, producirían estimadores sesgados de β de la variable de interés. Un segundo problema estadístico de usar MCO es la selección del número de variables de control, si este es corto o bajo también se producirían sesgos en la estimación y si este es alto o grande también se produciría errores de 'overfitting' (variables en excesos).[26]

El problema de endogeneidad o exogeneidad de una variable ha sido extensamente estudiada en la literatura y la solución estándar es la de variables instrumentales o mínimos cuadrados bi-etápicos (o TSLS, siglas en inglés). Sea Z_{it} la variable instrumental seleccionada, para que el estimador de β sea consistente con el método TSLS se requiere que[27]:

$$(A1) \qquad Cov\left(DCAL_{it}; Z_{it}\right) \neq 0; Cov\left(Z_{it}; \varepsilon_{it}\right) = 0$$

La expresión (A1) significa que el instrumento requiere estar correlacionado con la variable de interés y que además no esté asociado con el error estocástico de la especificación (1). La sección anterior ha mostrado estadísticos de 4 potenciales instrumentos con dos formas de medición de cada instrumento.[28] La consistencia del método TSLS será validada con la aplicación de tres pruebas estadísticas o 'tests'. Los dos primeros son las pruebas de 'idoneidad'

26 En términos simples el problema de 'overfitting' o sobreajuste de un modelo es una condición en la que un modelo estadístico comienza a describir el error aleatorio en los datos en lugar de las relaciones entre las variables. Este problema ocurre cuando el modelo es demasiado complejo. En el análisis de regresión, el sobreajuste puede producir valores de R-cuadrado, coeficientes de regresión y p-values engañosos.

27 Detalles en Lee, McCrary, Moreira, Porter (2022), Cunningham (2021) y Huntington-Klein (2022).

28 Una en forma binaria y la otra en porcentaje de empresas con la característica de la variable binaria por CIIU y año.

de Stock & Yogo (2005) y de Lee, McCrary, Moreira, Porter (2022). En el primer caso, la hipótesis nula es que el instrumento sea débil para la variable de interés[29]. En el segundo caso, la hipótesis nula es que la variable de interés no sea relevante en la determinación de la productividad laboral condicionado a que el instrumento seleccionado no sea débil para la variable de interés.[30] La tercera prueba es la de exogeneidad/endogeneidad tiene dos formas las de Wu (1974)-Haussman (1978) y la de Wooldridge (1995). En ambos casos, la hipótesis nula es que la variable de interés $DCAL_{it}$ sea exógena en la especificación (1).

Independientemente del problema de endogeneidad, la especificación (1) tiene aún los problemas de las confounding variables y el 'overfitting'. Para reducir las implicancias estadísticas de estos problemas, se implementa el método de Machine Learning causal de *Double/debiased machine learning*' o DML propuesto por Belloni, Chernozhukov, y Hansen (2014a, b), Chernozhukov, Chetverikov, Demirer, Duflo, Hansen, Newey, y Robins (2018, 2017)[31] y Baiardi A., A. Naghi (2020). Para ello, método utiliza las siguientes especificaciones:

(2) $$PL_{it} = \beta .DCAL_{it} + go\left(\vec{X}_{it}\right) + U_{it}\ ;\ i = 1,\ldots N; t = 2014 - 2019$$

(3) $$DCAL_{it} = mo\left(\vec{X}_{it}\right) + V_{it}$$

El vector $\vec{X}_{it}$ es el conjunto de covariables incluyendo potenciales variables confounding. U_{it} ; V_{it} ; y ε_{it} son los errores estocásticos de las tres especificaciones respectivamente. La metodología DML tiene los siguientes pasos[32]:

Paso 1 División de la Muestra. La muestra de los datos (INEI-ENE 2023) limpios se divide en las dos características de la variable binaria $DCAL$. La primera, cuando la empresa usa al menos una herramienta de gestión de calidad[33], $DCAL = 1$, durante el período de la muestra. La segunda cuando la em-

[29] $Ho: Cov\left(DCAL_{it}; Z_{it}\right) = 0$.

[30] $Ho: \beta = 0$.

[31] Los detalles técnicos del método se describen en estas dos contribuciones.

[32] Cabe señalar que el método DML requiere de una serie de supuestos, entre otros que: i) la covarianza entre el error estocástico de la ecuación (2) y la variable de interés $DCAL$ condicional al vector $\vec{X}_{it}$ sea cero; ii) el valor esperado del mismo error condicional a $DCAL$ y $\vec{X}_{it}$ sea cero; iii) la probabilidad que la variable $DCAL$, con valor uno, sea positiva o cero. En el caso que se use variables instrumentales Z, se adiciona los siguientes supuestos: iii) que cumpla (i) con los instrumentos; iv) que la covarianza entre el error U_{it} y el instrumento Z condicional a $\vec{X}_{it}$ sea cero; v) que exista una asociación entre la variable de interés y los instrumentos; vi) se cumpla (ii) condicional a Z y $\vec{X}_{it}$; y vii) que la covarianza entre $DCAL - E\left(DCAL / \vec{X}_{it}\right)$ y $DCAL / Z, \vec{X}_{it}$ - $E\left(DCAL / \vec{X}_{it}\right)$ no sea cero; (Ahrens, Hansen, Schaffer, Wiemann 2023).

[33] Las herramientas de gestión de calidad difieren entre períodos. En el primer periodo 2014-2017 se dispone de dos herramientas, normas técnicas y certificaciones y el segundo período 2014-2019 de tres herramientas, normas técnicas, certificaciones, y estanda-

presa no usa herramientas de calidad durante el periodo ($DCAL = 0$). Los estadísticos descriptivos de estos grupos de empresas se muestran en el Cuadro 2.

Paso 2 Grupos Muestrales. Para mayor precisión de las estimaciones del método DML se forma 2 grupos muestrales, K=2 y K=5. Luego se aplica el método DML a estos grupos, y el parámetro de interés de la variable de interés $DCAL$ es obtenido por el promedio de los estimados de los parámetros de la variable, lo cual es un estimador más robusto que los obtenidos con una sola una partición de la muestra.[34]

Paso 3 Estimaciones con el Método DML. El método DML y sus respectivos códigos de programación[35] se aplica a las especificaciones (2) y (3). El método tiene dos etapas. En la primera etapa se obtienen los estimadores 'debiased' ML usando herramientas de Machine Learning, ML, (por ejemplo LASSO[36]) de ambas ecuaciones y se estiman los respectivos errores $\hat{V}_{it}$ y $\hat{U}_{it}$ de las especificaciones [3.2] y [3.3]. Luego se realiza la regresión de $\hat{U}_{it}$ ($\hat{V}_{it}$) el cual produce el estimador del parámetro de interés β . En la segunda etapa, para obtener estimadores más robustos se realiza el siguiente procedimiento. Para cada par de muestras de los grupos establecidos en el paso anterior, se utiliza una de ellas, denominada grupo de muestra 'auxiliar' y se aplica la primera etapa del método DML, estimando $\widehat{go}$, $\hat{\beta}$', y $\widehat{mo}$. Luego, se estima el parámetro de interés $\hat{\beta}$ de la regresión $\hat{U}_{it}$ ($\hat{V}_{it}$), con los estimados de esos errores obtenidos de la segunda muestra denominada principal. El estimador del parámetro $\overline{\hat{\beta}}$ de la variable de interés se obtiene del promedio de los estimadores $\hat{\beta}$ de cada par de los K grupos.

Paso 4 Estimaciones del Método DML con Variables Instrumentales. Los códigos de programación del método DML también admiten estimaciones con variables instrumentales. En las sección anterior se presenta los indicadores de cuatro variables instrumentales cada una medida de dos formas, la binaria y en porcentajes de empresas por CIIU y año que poseen la característica de la variable binaria.

Para fines de *robustez*, aparte de los mínimos cuadrados ordinarios, MCO de la especificación para todas las variables, la de interés y las instrumentales juntamente con los MCO bi-etápicos, se estima el propensity score matching, PSM.

6. Estimaciones y Resultados

Desde la perspectiva teórica, Manjon & Mañez (2016) argumentan que las

rización.

34 Detalles en Baiardi & Naghi (2020) página 9.

35 Códigos DML (2023a) y DML (2023b).

36 Ahrens, Hansen, Schaffer (2019) y Códigos PDLASSO (2023).

empresas toman decisiones dinámicas sobre un conjunto de factores, que influyen el presente y futuro de sus rentabilidades, y decisiones temporales sobre otro conjunto de factores que no necesariamente influyen en dichas rentabilidades. El número de trabajadores, así como las decisiones de inversión son factores que influirán en el flujo de sus rentabilidades en el tiempo. Los gastos en materiales y de energía no los influirán. En consecuencia, la definición de empresas por número de trabajadores tendrá incidencia sobre las rentabilidades y por ende sobre las productividades de las empresas. Caso contrario ocurre con la definición del tamaño de las empresas por ventas. En esencia estas variables pueden convertirse en variables endógenas que influirán el resultado de las estimaciones. A consecuencia de lo anterior, las estimaciones que se presentan corresponden a los tres primeros criterios de definición de tamaño de empresas: el basados en el número de trabajadores y los dos primeros criterios basados en ventas. Los resultados de las estimaciones con los dos últimos criterios (por tamaño y ventas), por un lado, reducen el tamaño de la muestra, y de otro lado, no producen resultados estadísticamente robustos. Estas estimaciones no son reportadas en el trabajo. Por los argumentos teóricos señalados, los resultados más robustos (estadísticamente) son los que definen el tamaño de las empresas por el número de trabajadores.

6.1 Regresiones MCO

Los análisis econométricos tradicionales o estándar se basan el método de mínimos cuadrados ordinarios. Sin embargo, para que este método produzca inferencias causales es necesario que las variables de interés ($DCAL_{it}$) y de control (X_{it}) en la especificación (1) sean variables exógenas. Por los argumentos teóricos formulados en las secciones anteriores y por los resultados de las pruebas estadísticas de la sección 6.2, se verifica que el método no produce dichas inferencias causales. Como consecuencia requiere usarse otros métodos como los descritos en la 6.4.

Los Cuadros del A3 al A8, disponibles al lector, señalan las deficiencias de las estimaciones estándar por MCO (mínimos cuadrados ordinarios) de la ecuación (1)[37] donde el coeficiente de la variable interés $DCAL_{it}$ varía en signo y significancia estadística de acuerdo con la definición del tamaño de la empresa, y consecuentemente no produce resultados claros. Los coeficientes de la variable de interés y sus potenciales instrumentos revelan con claridad que los resultados de los criterios de Ventas 1 y 2 no son estadísticamente confiables tanto en signo como en la significancia estadística de los coeficientes de dichas variables. Contrariamente, los coeficientes estimados por MCO de la variable de interés y sus potenciales instrumentos en la definición de tamaño

[37] La variable dependiente de la productividad y el ratio capital- trabajo están en logaritmo neperiano.

por el número de trabajadores[38] son positivos y la mayoría estadísticamente significativos en las muestras de los dos periodos.[39] Independientemente del criterio de tamaño de empresa, otros factores también incidieron positivamente sobre la productividad y de manera robusta. Estos son: el ratio capital-trabajo ($lnk \; y \; DC$)[40]; las empresas que exportan (DX), uso de tecnología de punta ($DTEC_1$), el tamaño de las empresas (grandes y medianas) y en menor medida empresas con operaciones de dos o más turnos ($DTurn_2$). Los coeficientes de los demás factores no tienen robustez estadística en ambos períodos.

6.2 Pruebas de Exogeneidad (Endogeneidad) con Diferentes Instrumentos

Dado los argumentos teóricos de endogeneidad de la variable de interés $DCAL_{it}$ que evita inferencias causales si se usa el método MCO, las cifras de los cuadros, disponibles lector (del A9 al A11) indican los estadísticos de las pruebas sobre la endogeneidad/exogeneidad de la variable de interés y sobre la idoneidad de las ocho variables instrumentales seleccionadas. Las cifras indican, que para la definición del tamaño de las empresas, la mayoría de las variables instrumentos son endógenas. Sin embargo, las pruebas de idoneidad[41] de las variables instrumentales señalan que sólo la características de orden de compra digital por parte de las empresas en sus dos medidas ($DOCDg \; y \; DOCDg \,\&\, CIIU$) resultaran variables instrumentales idóneas para la variable de interés en ambos períodos. Los resultados para las definiciones del tamaño de la empresa por ventas son estadísticamente menos robustas comparados con aquellos resultantes de la definición de tamaño por el número de trabajadores.

6.3 Estimaciones de Regresiones Bi-etápicas (TSLS)

Dado los resultados de las pruebas de endogeneidad y de idoneidad de los instrumentos asociados a la variable de interés ($DCAL_{it}$), se supone que el método de variables instrumentales o regresiones de MCO bi-etápicos (o two stage least squares, TSLS, en inglés) producen inferencias causales. Sin embargo, por la posible existencia de variables confounding y la posibilidad de

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38 Cuadros A3 y A5 disponibles al lector.

39 Para ambos períodos, sólo el coeficiente de la variable instrumental, de que la empresa percibe con diferenciación y calidad en los productos puede competir (DCALDIF), no es estadísticamente significativo. Todos los demás coeficientes de las variables (la de interés y el resto de las variables instrumentales) son estadísticamente significativos e inciden positivamente sobre la productividad de las empresas.

40 DC es una variable binaria que toma el valor de uno si no existe información del ratio de capital-trabajo, y cero de otra manera. Si esta variable es uno entonces $lnk = 0$.

41 Los tests de Stock & Yogo (2005) y de Lee et al (2022).

introducir una extensa lista de variables de control (X_{it}), la inferencia causal de la variable de interés aun no es posible con el método TSLS. Las estimaciones (disponibles al lector en los Cuadros del A12 al A17) evidencian dicha posibilidad. En líneas generales, los resultados son menos robustos estadísticamente que los coeficientes del método MCO. Sin embargo, para las variables instrumentales idóneas ($DOCDg\ y\ DOCDg\ \&\ CIIU$), los resultados son relativa y estadísticamente mejores, particularmente para el segundo período 2014-2019. Así, las variables instrumentales tienen efectos positivos y estadísticamente significativos sobre la productividad laboral. De igual manera, los coeficientes de las variables tamaño de la empresa, el ratio capital-trabajo y la propensión a exportar de las empresas son estadísticamente significativas y aparentemente estas variables inciden la productividad laboral de las empresas.

6.4 Resultados del Método DML y Alternativos

Las deficiencias en inferencias causales que producen los métodos MCO y TSLS son reducidas con el método DML. Este método que introduce métodos de 'machine learning' combinado con un óptimo número de variables de control (regresiones regularizas) reducen las deficiencia de los métodos señalados y pueden sustentar inferencias causales. Los resultados que se presentan aquí validan esta afirmación.

La idea intuitiva del método DML es la siguiente, en la medida que se aumenta el número de variables de control X_{it} en las ecuaciones (2) y (3) podemos reducir el efecto de las variables confusas. De otro lado, el número de variables de control X_{it} puede ser reducida a través de regresiones regularizadas de Lasso.[42] Cuando se aplican estas técnicas a (2) y (3), los errores estimados correspondientes $\hat{U}_{it}$ y $\hat{V}_{it}$ se interpretan como la productividad y el instrumento de gestión de calidad netos de las variables de control y por consiguiente la regresión de $\hat{U}_{it}$ ($\hat{V}_{it}$) mide el efecto neto de la herramienta de gestión de calidad ($DCAL_{it}$) sobre la productividad laboral de la empresa (PL_{it}).

Las estimaciones DML de los efectos de la variable de interés y sus instrumentos sobre la productividad laboral se presentan en los Cuadros del 5 al 7. Las cifras señalan, por un lado, que existe una 'inferencia causal' de las variables instrumentales idóneas ($DOCDg\ y\ /\ o\ DOCDg\ \&\ CIIU$) de la variable de interés $DCAL$ sobre la productividad laboral de las empresas. Esta conclusión es estadísticamente robusta. De otro lado, las empresas que usan por lo menos una herramienta de gestión de calidad tienen una productividad laboral mayor en el rango entre 33% y 39% que las empresas que no usan herramientas de

42 En inglés 'least absolute shrinkage and selection operator', operador de selección y de menor reducción absoluta, en castellano.

gestión de calidad[43] en los dos períodos de análisis. El método PMS sirve solo de complemento al método DML. Este método evidencia la deficiencia estadística de usar a las ventas como criterio para definir tamaño de la empresa para un análisis inferencial de causalidad entre la productividad laboral de las empresas y los instrumentos de gestión de calidad. Los resultados de aplicar el PMS son menos robustas con la definición de tamaño de empresas basada en ventas (1 y 2) que los resultados que se obtienen con la definición de empresas basada en número de trabajadores.

43 Cifras de acuerdo con el método PMS usando la definición de tamaño de la empresa por número de trabajadores.

TABLA 5

ESTIMACIONES DML Y PMS: POOL 2014 - 2019

Variables	**2014-2017**		**2014-2019**	
	K=2	**K=5**	**K=2**	**K=5**
DML-IV				
DCAL	0.266*** (0.086)	0.272*** (0.087)	0.228*** (0.064)	0.240*** (0.064)
IV – DCALDIF	0.0273 (2.219)	-0.0309 (1.997)	-0.209 (4.881)	0.915 (3.927)
IV – DCALDIF & CIIU	-3.802* (1.970)	-3.698* (1.948)	-10.79 (16.01)	-8.877 (10.86)
IV – DMIL	-2.965 (2.272)	-2.800 (2.227)	-14.98 (27.63)	-13.31 (25.67)
IV – DMIL & CIIU	-12.51 (10.91)	-15.53 (15.64)	3.916 (2.479)	5.096 (3.193)
IV – DIMB	-3.488 (3.812)	-3.952 (4.411)	-7.621 (13.49)	-9.671 (21.17)
IV – DIMB & CIIU	-6.219** (2.896)	-6.443** (2.884)	11.59 (8.937)	13.34 (11.70)
IV – DOCDg	1.631** (0.729)	1.981** (0.884)	2.771*** (0.914)	2.688*** (0.936)
IV – DOCDg & CIIU	5.716*** (1.585)	6.315*** (1.806)	4.700*** (1.272)	4.928*** (1.403)
PMS (K=1)				
DCAL	37629.1*** (11608.68)		37055.89*** (6689.945)	
DCALDIF	-3885 (8682)		10,307 (10119)	
DMIL	-602.8 (12114)		-6,090 (8114)	
DIMB	8,506 (11,797)		20095*** (7369)	
DOCDg	21826** (10585)		27403** (11450)	

Fuente: INEI-ENE (2023), Cuadro A1. Elaboración propia. K = 1 para las estimaciones de PMS, Lasso y de Lasso-IV. ND: No disponible.

TABLA 6 (VENTAS 1)

ESTIMACIONES DML Y PMS: POOL 2014- 2019

Variables	2014-2017		2014-2019	
	K=2	K=5	K=2	K=5
DML-IV				
DCAL	-0.0234 (0.0986)	-0.0353 (0.0993)	0.0197 (0.0608)	0.0272 (0.0603)
IV – DCALDIF	-1.502 (1.090)	-1.450 (1.187)	-4.715 (3.431)	-4.335 (3.239)
IV – DCALDIF & CIIU	-2.464*** (0.878)	-2.275*** (0.861)	-5.609** (2.582)	-5.695** (2.737)
IV – DMIL	-2.670 (1.899)	-2.890 (1.917)	-8.751 (10.64)	-7.404 (7.481)
IV – DMIL & CIIU	-3.989** (1.762)	-3.656** (1.664)	17.26 (27.70)	14.61 (20.99)
IV – DIMB	-1.833 (3.769)	-1.382 (3.399)	-4.439 (11.47)	-4.724 (11.97)
IV – DIMB & CIIU	-3.268*** (1.130)	-3.151*** (1.082)	-62.39 (238.8)	-53.97 (175.8)
IV – DOCDg	-0.398 (0.613)	-0.323 (0.589)	-0.799 (0.616)	-0.814 (0.654)
IV – DOCDg & CIIU	6.878** (3.175)	6.440** (2.912)	3.590*** (1.315)	3.820*** (1.431)
PMS (K=1)				
DCAL	0.0168 (0.107)		0.0584 (0.0842)	
DCALDIF	0.00838 (0.0960)		-0.0831 (0.0964)	
DMIL	0.0580 (0.0818)		0.154** (0.0745)	
DIMB	0.0105 (0.129)		0.0629 (0.129)	
DOCDg	-0.130 (0.123)		-0.300** (0.147)	

Fuente: INEI-ENE (2023), Cuadro A1. Elaboración propia. K = 1 para las estimaciones de PMS, Lasso y de Lasso-IV. ND: No disponible.

TABLA 7 (VENTAS 2)

ESTIMACIONES DML Y PMS: POOL 2014 - 2019

Variables	**2014-2017**		**2014-2019**	
	K=2	**K=5**	**K=2**	**K=5**
DML-IV				
DCAL	-0.322*** (0.0930)	-0.339*** (0.0949)	-0.150*** (0.0577)	-0.145** (0.0573)
IV – DCALDIF	-5.252** (2.344)	-5.306** (2.539)	-10.68 (8.860)	-9.812 (7.683)
IV – DCALDIF & CIIU	-5.203*** (1.354)	-4.905*** (1.276)	-13.83* (7.884)	-13.90* (7.947)
IV – DMIL	-2.189 (1.431)	-2.366 (1.454)	-7.668 (7.329)	-8.442 (8.969)
IV – DMIL & CIIU	-7.293*** (2.737)	-6.595*** (2.381)	13.19 (10.80)	14.21 (12.42)
IV – DIMB	0.317 (2.213)	0.472 (2.295)	-1.219 (5.523)	-1.077 (4.841)
IV – DIMB & CIIU	-4.383*** (1.232)	-4.078*** (1.113)	71.82 (248.0)	6,486 -1957000.00
IV – DOCDg	-4.068*** (1.068)	-3.948*** (1.039)	-4.460*** (1.012)	-4.596*** (1.097)
IV – DOCDg & CIIU	6.085* (3.412)	5.870* (3.354)	3.027** (1.205)	3.357** (1.365)
PMS (K=1)				
DCAL	-0.318*** (0.103)		-0.112 (0.0827)	
DCALDIF	-0.257*** (0.0815)		-0.253*** (0.0818)	
DMIL	0.0587 (0.0768)		0.105 (0.0708)	
DIMB	-0.0791 (0.112)		0.00212 (0.111)	
DOCDg	-0.285** (0.122)		-0.471*** (0.133)	

Fuente: INEI-ENE (2023), Cuadro A1. Elaboración propia. K = 1 para las estimaciones de PMS, Lasso y de Lasso-IV. ND: No disponible.

7. Conclusiones

Basado en los enfoques conceptuales de la teoría de la gestión de calidad total (TQM) y de Syverson (2011), este trabajo utiliza técnicas de 'machine learning' para determinar la inferencia causal del uso de las herramientas de gestión de calidad sobre las empresas peruanas en el período 2014-2019. La base de datos proviene de la Encuesta Nacional de Empresas del INEI del periodo 2015-2020[44] (INEI-ENE 2023). La metodología aplicada puede ser útil en los casos en que métodos estándar (como MCO Y TSLS) no produzcan resultados estadísticamente confiables. Luego de una limpieza de los datos, se usó una muestra donde cerca del 50% de las firmas de la muestra son empresas grandes (que emplean de 100 más trabajadores), lo cual sugiere que los resultados tienen una mayor aplicabilidad a las empresas grandes (y en menor medida a empresas medianas) que a las pequeñas.

Luego de la implementación de una batería de métodos y pruebas estadísticas, la conclusión más robusta para los dos períodos considerados, particularmente para la definición del tamaño de las empresas por el número de trabajadores, es que las herramientas de gestión de calidad sirven para incrementar la productividad laboral de las empresas, particularmente para las empresas grandes y medianas y del sector manufacturero las cuales también dominan la muestra.

Teóricamente existen una serie de mecanismos mediante los cuales los instrumentos de gestión de calidad pueden mejorar la productividad laboral de las empresas. Entre los más relevantes figuran el incremento o establecimiento de reputación del producto por los consumidores lo cual incrementa o sostiene las ventas de la empresa; reducción de los costos de producción debido a que las herramientas de gestión de calidad pueden producir productos menos defectuosos y con menos demoras en el proceso de producción; y el hecho que la calidad reduce la reelaboración de los productos incrementando así la productividad.[45] Los resultados econométricos son consistentes con otros estudios[46] del sector manufacturero, los cuales también señalan que el ratio capital-trabajo y la propensión a exportar son factores que influyen en la productividad laboral de las empresas.

A pesar de la potenciales limitaciones del método DML utilizado[47], este estudio avanza y contribuye con respecto a previos estudios encontrados en la literatura empírica en cinco aspectos: provee un marco conceptual de las

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44 La cual corresponde a los años del 2014 al 2017 y 2019.

45 Detalles en Harrington (1991), https://www.indeed.com/career-advice, Lakhe & Mohanty (1994) y Figura 1.

46 Por ejemplo, Tello (2021, 2020, 2017 y 2015).

47 Por ejemplo los descritos en Wang, Sapino, Wook-Shin, El Abbadi, Dobbie, Feng, Shao, y Yin (2023) y Utamayz, Moosaviz, y Gurevychz (2020).

relaciones entre instrumentos de calidad y la productividad laboral basado en ventas reales por trabajador de las empresas; realiza pruebas de exogeneidad de la variable de interés que sirve para la posibilidad de realizar inferencias causales; identifica instrumentos adecuados basados en tres tipos de pruebas; y (basado en la técnica DML) aborda los problemas de las variables confusas y el uso de excesivo de variables de control. De los resultados se percibe ausencias que requieren ser abordadas en futuras investigaciones. Por un lado, se requiere muestras de empresas que contengan información que permita medir los impactos de los otros dos insumos de la TQM, el compromiso de la gerencia en la gestión de calidad, y la efectividad del trabajo en equipo y participación de los gerentes en dicha gestión. Por otro lado, se requiere analizar los efectos separados, y no en conjunto, de los instrumentos de gestión de calidad que tienen propósitos distintos y particulares, y el rol de la participación extranjera en la determinación de la productividad de las empresas.

Referencias

Ahrens, A., C. Hansen, M. Schaffer, T. Wiemann (2023). "Double/Debiased Machine Learning in Stata". IZA DP No. 15963.

Albulescu, C. T., A. Drăghici, G. M. Fistiş, and A. Truşculescu. (2016). "Does ISO 9001 quality certification influence labor productivity in EU-27?" Procedia-Social and Behavioral Sciences, 212, pp.78-286. https://doi.org/10.1016/j.sbspro.2016.05.116

Ahrens, A., C. Hansen, Mark Schaffer (2019). "Lassopack: Model selection and prediction with regularized regression in Stata: Econ EM". https://doi.org/10.2139/ssrn.3323196

Baiardi A., A. Naghi (2020). "The Value Added of Machine Learning to Causal Inference: Evidence from Revisited Studies". arXiv.org blog, Cornell University. https://doi.org/10.2139/ssrn.3759867

Belloni, A., V. Chernozhukov, C. Hansen (2014a). "Inference on Treatment Effects after Selection amongst High-Dimensional Controls". *Review of Economic Studies*, Vol. 81, No. 2, pp. 608-650. https://doi.org/10.1093/restud/rdt044

Belloni, A., V. Chernozhukov, C. Hansen (2014b). "High-Dimensional Methods and Inference on Structural and Treatment Effects". *Journal of Economic Perspectives*, Vol. 28, Nor 2, pp. 29-50. https://doi.org/10.1257/jep.28.2.29

Bernini, F.; Figal Garone, L. and A. Maffioli (2017). "Certificación Internacional de Calidad: ¿Señalizando a quién? Impacto en el desempeño de empresas en Argentina". IDB WP 770.

Bernini, F., L. Garone, A. Maffioli, and A, Mena. (2019). "Global value chains: Can quality certifications improve local firms' integration? Evidence from Latin America and the Caribbean". Mimeo.

Bewoor, A. K., and M. S. Pawar. (2010). "An empirical analysis of impact of QMS/ISO implementation on productivity/performance of Indian SMEs". *International Journal of Industrial Engineering and Technology*, 2(1), 85-109.

Castro-Silva, H. F., and F. Rodríguez. (2017). "Incidencia de la certificación de la norma ISO 9001 en los resultados empresariales. Un caso colombiano". *Entre Ciencia e Ingeniería*, 11(22), 18-25. https://doi.org/10.31908/19098367.3545

Chernozhukov, V., D. Chetverikov, M. Demirer, E. Duflo, C. Hansen, W. Newey, J. Robins (2018). "Double/debiased machine learning for treatment and structural parameters". *Econometrics Journal*, volume 21, pp. C1-C68. doi: 10.1111/ectj.12097.https://doi.org/10.1111/ectj.12097

Chernozhukov, V., D. Chetverikov, M. Demirer, E. Duflo, C. Hansen, W. Newey, J. Robins (2017). "Double/Debiased/Neyman Machine Learning of Treatment Effects". Papers and Proceedings, *American Economic Review*, Vol. 107, No. 5, pp 261-265.
https://doi.org/10.1257/aer.p20171038

Cunningham, S. (2021). *Causal Inference: The Mixtape*. Yale University Pres New Haven & London. https://doi.org/10.12987/9780300255881

Deming, W. E. (1993). *The New Economics For Industry*, *Government & Education*. Cambridge: Massachusetts Institute of Technology Center for Advanced Engineering Study.

Dotchin, J. J. S. Oakland (1992). *Theories and concepts in total quality management, Total Quality Management*, 3:2, 133-146

Fatima, M. (2014). "Impact of ISO 9000 on business performance in Pakistan: Implications for quality in developing countries". *Quality Management Journal*, 21(1), 16-24. https://doi.org/10.1080/10686967.2014.11918373

FAO (2003). *Environmental and Social Standards, Certification and Labelling for Cash Crops*. Food & Agriculture Organization.

Gallego, J. M., and L. H. Gutiérrez. (2021). "Quality certification and firm performance. The mediation of human capital. International" *Journal of Productivity and Performance Management*. https://doi.org/10.1108/IJPPM-12-2020-0643

Gallego, J. M., and L. H. Gutiérrez. (2017). "Quality management system and firm performance in an emerging economy: The case of Colombian manufacturing industries". Inter-American Development Bank Institutions for Development Sector, Serie No. IDB-WP-80 3, pp. 1-28, https://doi.org/10.18235/0000686

Goedhuys, M., & Sleuwaegen, L. (2013). "The Impact of International Standards Certification on the Performance of Firms in Less Developed Countries". *World Development* Vol. 47, pp. 87-101. https://doi.org/10.1016/j.worlddev.2013.02.014

Harrington H.J. (1991). *Business Process Improvement: The Breakthrough' Strategy for Total Quality*, Productivity. Quality Press.

Häversjö, T. (2000). "The financial effects of ISO 9000 registration for Danish companies". *Managerial Auditing Journal*, 15(1/2), 47-52. https://doi.org/10.1108/02686900010304632

Hausman, J. A. (1978). "Specification tests in econometrics". *Econometrica 46*, pp. 1251-1271. https://doi.org/10.2307/1913827

Heras, I., F. Marimon, M. Casadesús (2010). "Impact of quality improvement tools on the performance of firms using different quality management systems". *Revista Innovar*. 21-42, 161-173.

Heras, I., G. P. M. Dick, and M. Casadesús (2002). "ISO 9000 Registration's Impact on Sales and Profitability: A Longitudinal Analysis of Performance Before and After Accreditation". International *Journal of Quality & Reliability Management* 19 (6): 774-91. https://doi.org/10.1108/02656710210429618

Huntington-Klein, N. (2022). *The Effect: An Introduction to Research Design and Causality*. Taylor & Francis Group. https://doi.org/10.1201/9781003226055

Ilkay, M. S., and E. Aslam. (2012). "The effect of the ISO 9001 quality management system on the performance of SMEs". *International Journal of Quality & Reliability Management*. Vol. 29 Iss. 7 pp. 753 - 778. https://doi.org/10.1108/02656711211258517

Islam, M. M., M. A. Karim and E. M. Habes. (2015). "Relationship between quality certification and financial & non-financial performance of organizations". *The Journal of Developing Areas*, 49(6), 119-132. https://doi.org/10.1353/jda.2015.0079

Jiménez-Jiménez, D., M. Martínez-Costa, A. Martínez-Lorente, H. Ahmed Dine Rabeh (2015). "Total quality management performance in multinational companies; A learning perspective". *The TQM Journal*, Vol. 27-3 pp. 328 – 340. http://dx.doi.org/10.1108/TQM-01-2014-0002

Juran, J., B. Godfrey, R. Hoogstoel, E. Schilling (1999). *Juran's Quality Handbook*. McGraw-Hill.

Kiplagat, R. J. (2013). *Impact of ISO 9001 certification on financial performance of commercial state corporations in Kenya* (Doctoral dissertation, University of Nairobi).

Klosin S., M. Vilgalys (2022). "Estimating Continuous Treatment Effects in Panel Data using Machine Learning with an Agricultural Application". MIT mimeo.

Koskela, L., Tezel, A., and Patel, V. (2019). *Theory of Quality Management: its Origins and History. Proc. 27th Annual Conference of the International*. Group for Lean Construction (IGLC), Pasquire C. and Hamzeh F.R. (ed.), Dublin, Ireland, pp. 1381-1390 DOI: https://doi.org/10.24928/2019/0259.

Lakhe R., R. Mohanty (1994). "Total Quality Management Concepts, Evolution and Acceptability in Developing Economies". *International Journal of Quality & Reliability Management*, Vol. 11 No. 9, pp. 9-33.

Lee, D., J. McCrary, M. Moreira, J. Porter (2022). "Valid t -Ratio Inference for IV". *American Economic review*, 112-10, pp. 3260-3290 https://doi.org/10.1257/aer.20211063

Manjon, M., J. Mañez 2016. "Production function estimation in Stata using the Ackerberg-Caves-Frazer method". *The Stata Journal* 16-4, pp. 900-916. https://doi.org/10.1177/1536867X1601600406

Mauch, P. (2010). *Quality Management Theory and Application*. Taylor & Francis.

Mena, A., (2020). *The impact of Quality Certifications on firms' performance. A Random Forest Diff-in-Diff approach*. Tesis de Maestría Universidad San Andrés, Argentina.

Nagpal, A. (2017). "L1 and L2 Regularization Methods of Machine Learning". Disponible en https://towardsdatascience.com/l1-and-l2-regularization-methods-ce25e7fc831c

Saizarbitoria, I. H., and G. A. Landín. (2011). "Impacto de la certificación ISO 14001 en el rendimiento financiero empresarial: conclusiones de un estudio empírico". *Cuadernos de Economía y Dirección de la Empresa*, 14(2), 112-122. https://doi.org/10.1016/j.cede.2011.02.002

Sánchez-Ollero, J. L., A García-Pozo and M, Marchante-Lara. (2015). "Measuring the effects of quality certification on labor productivity: An analysis of the hospitality sector". *International Journal of Contemporary Hospitality Management*, Vol. 27 Issue: 6, pp.1100-1116 https://doi.org/10.1108/IJCHM-02-2014-0057

Samuel, Arthur (1959). "Some Studies in Machine Learning Using the Game of Checkers". IBM *Journal of Research and Development*. 3 (3): 210-229. https://doi.org/10.1147/rd.33.0210

Starke, F.; R. Eunni, N. Dias Fouto, C.de Angelo. (2012). "Impact of ISO 9000 certification on firm performance: evidence from Brazil". *Management Research Review* 35:10, 974-997. https://doi.org/10.1108/01409171211272697

Stock, James H., and M. Yogo. (2005). "Testing for Weak Instruments in Linear IV Regression". In *Identification and Inference in Econometric Models: Essays in Honor of Thomas J. Rothenberg, edited by Donald*

W.K. Andrews and James H. Stock, capítulo 5, pp. 80-108. Cambridge: Cambridge University Press.
https://doi.org/10.1017/CBO9780511614491.006

Svverson, C. (2011). "What determines productivity?". *Journal of Economic Literature*. https://doi.org/10.1257/jel.49.2.326

Tetteh, E., B. Uzochukwu (2015). *Lean Six Sigma Approaches in Manufacturing, Services, and Production*, Capitulo 1, Business Science Reference (an imprint of IGI Global).

Tello, M.D. (2021). "Effects of obstacles to Innovation: Are They Complementary?" *Journal of Innovation Economics & Management*. 2021/2 n° 35 | pages 187- 217. https://doi.org/10.3917/jie.pr1.0094

Tello, M.D. (2020). "Investigación & Desarrollo, Tecnologías de Información y Comunicación e Impactos sobre el Proceso de Innovación y la Productividad". WP-487, department of economics, PUCP.
https://doi.org/10.18800/2079-8474.0487

Tello, M.D. (2017). "Firms' innovation and productivity in services and manufacturing: the case of Peru". *CEPAL Review*, No 121, April.
https://doi.org/10.18356/a4c7eea5-en

Tello, M.D. (2015). "Firms' Innovation, Public Financial Support and Total Factor Productivity: The Case of Manufactures in Peru". *Review of Development Economics*. 19(2), 358-374.
https://doi.org/10.1111/rode.12147

Terziovski M.; D. Samson, D. Dow (1997). "The business value of qualify management systems certification: evidence from Australia and New Zealand". *Journal of Operations Management*. Vol. 15 No1 pp 1-18.
https://doi.org/10.1016/S0272-6963(96)00103-9

Tzelepis, D., K. Tsekouras, D. Skuras, E. Dimara (2006). "The effects of ISO 9001 on firms' productive efficiency". *International Journal of Operations & Production Management*, Vol. 26 No. 10, pp. 1146-1165.
https://doi.org/10.1108/01443570610691111

Utamayz, P., N. Moosaviz, I. Gurevychz (2020). "Mind the Trade-off: Debiasing NLU Models without Degrading the In-distribution Performance". *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 8717–8729

Vargas, F. (2016). "The role of quality certification and innovation as sources of productivity growth in Peru". UNU-MERIT and Maastricht University.

Wang, X., M. Sapino, H. Wook-Shin, A. El Abbadi, G. Dobbie, Z. Feng, Y, Shao, H. Yin (Eds.) (2023). *Database Systems for Advanced Applications: 28th International Conference*, DASFAA, Tianjin, China, 2023, Proceedings, Part IV.

Wayham, V., E. Kirche, B. Khumawala (2002). "ISO 9000 certification:

financial performance implications". *Total Quality Management*, VOL. 13, NO. 2, 2002, 217- 231.https://doi.org/10.1080/09544120120102450

Wooldridge, J. M. (1995). "Score diagnostics for linear models estimated by two stages least squares". In *Advances in Econometrics and Quantitative Economics: Essays in Honor of Professor C. R. Rao*, ed. G. S. Maddala, P. C. B. Phillips, and T. N. Srinivasan, 66–87. Oxford: Blackwell

Wu, D.-M. (1974). "Alternative tests of independence between stochastic regressors and disturbances: Finite sample results". *Econometrica* 42, pp 529–546. https://doi.org/10.2307/1911789.

Zhang, Z (2000). *Implementation of Total Quality Management An Empirical Study of Chinese Manufacturing Firms*. University of Groningen. The Netherlands.

Zhang Z (1997). *Developing a TQM Quality Management Method Model*. University of Groningen. The Netherlands.

Zhanga, Z, J. Song, J. Song (2014). "Analysis of relationship between quality management system and design assurance system". *Procedia Engineering* 80 pp. 565 – 572. doi: 10.1016/j.proeng.2014.09.112

Fuentes de Información

BCRP (2023). *Estadísticas Económicas*. www.bcrp.gob.pe. Banco Central de Reserva del Perú.

INEI-ENE (2023). Encuesta Nacional de Empresas, varios años. Instituto Nacional de Estadística e Informática. Disponible en: https://ogeiee.produce.gob.pe/index.php/en/shortcode/normatividad-metodologia-oee/encuesta-nacional-de-empresas

PRODUCE-INACAL (2018). *Primera Encuesta Nacional de Calidad a MYPE Manufactureras 2017*. Disponible en: https://www.inacal.gob.pe/principal/categoria/estudios-investigacione-oee

Códigos DML (2023a). Disponible en https://paperswithcode.com/paper/doubledebiased-machine-learning-for-treatment

Códigos PDLASSO (2023). "PDSLASSO: Stata module for post-selection and post-regularization OLS or IV estimation and inference". Achim Ahrens-Christian B. Hansen-Mark E Schaffer. Disponibles en https://ideas.repec.org/c/boc/bocode/s458459.html (y download).

DML (2023b). Disponibles en: https://www.youtube.com/watch?v=eHOjmyoPCFU (Victor Chernozhukov) y https://docs.doubleml.org/stable/index.html

Beyond formal R&D: firm's capabilities and its innovation profile. The case of Argentinean manufacturing firms (2014-2016)

Más allá de la I+D formal: capacidades de la firma y perfil de innovación. El caso de las empresas manufactureras argentinas (2014-2016)

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Abstract

The purpose of this article is to analyse the relationship between different innovation profiles, capabilities, and innovation results of manufacturing firms from Argentina. The premise that guides our research is that most of firms not performing formal R&D -92%- are a highly heterogeneous group in terms of innovative behaviour, capabilities and innovative performance. Thus, we propose to study firms' innovation profile as a gradient that accounts for formal R&D, informal R&D, non- R&D performing firms and firms without innovation efforts. Then, the relationship between these profiles and five dimensions of firms' capabilities -productive, organizational, connectivity, and accumulated and potential absorptive - is explored. Accordingly, the study of how these profiles correlate with firms' innovation results -products and/or processes innovations, new marketing and/or organizational changes, patents and ratio of new product sales to total sales- is also carried out. The empirical evidence is based on Argentinean manufacturing firms with data from the second wave of the National Innovation Survey composed by around 4000 observations for the period of 2014-16. Results suggest that more complex R&D profiles require higher levels of capabilities. Moreover, there seems to be a threshold of capabilities in moving from the non-R&D to the informal R&D profile. Likewise, while informal R&D is a critical threshold to increase the probability of obtaining product, process, organization and marketing innovations, formal R&D is key to get patents and to increase the share of new products on total sales.

Key words: *Innovation profile; capabilities; innovation results; manufacturing firms; Argentina.*

JEL Classification: *D21, D22, O30.*

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Resumen

El objetivo de este artículo es analizar la relación entre diferentes perfiles de innovación, capacidades y resultados de innovación en las empresas manufactureras argentinas. La premisa que guía la investigación es que la mayoría de las empresas que no desarrollan I+D -92%- son un grupo altamente heterogéneo en términos de comportamiento innovativo, capacidades y desempeño innovador. Así, proponemos estudiar el perfil de innovación de las empresas como un gradiente que incluye I+D formal, I+D informal, firmas que no realizan I+D y firmas que no realizan esfuerzos en innovación. De esta forma, es explorada la relación entre esos perfiles y cinco dimensiones de capacidades de la firma -productivas, organizacionales, de conectividad y de absorción acumulada y potencial-. Asimismo, se estudia cómo estos perfiles correlacionan con los resultados de innovación de la firma -innovaciones de producto y/o proceso, marketing y/o cambios organizacionales, patentes y ratio de nuevos productos sobre el total de ventas-. La evidencia empírica se basa en las empresas manufactureras argentinas, con datos de la segunda vuelta de la Encuesta Nacional de Innovación, que contiene alrededor de 4000 observaciones para el período 2014-16. Los resultados sugieren que los perfiles más complejos de I+D requieren mayores niveles de capacidades. Más aun, parece existir un umbral mínimo de capacidades para trasladarse del perfil que no realiza I+D al perfil de I+D informal. De la misma manera, mientras realizar I+D informal es un umbral fundamental para aumentar la probabilidad de obtener innovaciones en producto, proceso, organizacional y de marketing, la I+D formal es clave para obtener patentes y para aumentar la proporción de nuevos productos en el total de ventas.

Palabras clave: *Perfil de innovación; capacidades; resultados de innovación; firmas manufactureras; Argentina.*

Clasificación JEL: *D21, D22, O30.*

1. Introduction

The objective of this paper is to analyze the relationship between firm's capabilities, innovation profiles and innovation results. Within evolutionary theory of innovation, firms' innovative behavior depends on multiple sources of knowledge and learning that go beyond formal R&D (e.g.: Dosi, 1988; Freeman, 1974; Nelson and Winter, 1982; Pavitt, 1984; Rosenberg, 1982). Thus, capabilities matter as much as innovation efforts when trying to explain innovation results and economic performance. Nevertheless, most empirical contributions consider that formal R&D plays an exclusive role in explaining innovation efforts and results (Arundel et al., 2007). Much of this literature gives a secondary role to both the rest of innovative efforts –e.g.: acquiring capital goods, quality assurance, training, engineering and design- and firms' different types of capabilities (e.g.: Crepon et al., 1998; Hall et al., 2010; Verspagen, 1995).

To a large extent, this wide empirical literature is based on the availability of information arising from R&D indicators, mainly based on the recommendations of Frascati and Oslo manuals (OECD, 2002, 2005, 2018). In this regard, traditional definitions of R&D followed by these manuals pay more attention to "the systematic search for new knowledge from basic and applied science", than to "experimental development processes", not necessarily carried out within R&D labs (Arundel et al., 2007). This is at odds with the fact that within evolutionary literature these informal processes of problem-solving are recognized as key elements in generating innovations. Even worse, public policy has been focused on the promotion of formal R&D as well, which has also narrowed the scope of beneficiaries to high technological intensity industries (Fiorentin, Pereira and Suarez, 2018).

In other words, theoretical analysis, statistical indicators, and innovation policy were biased towards Jensen's et al (2007) "science, technology and innovation (STI) learning mode", which is based on the generation of scientific and technological knowledge through R&D activities. Conversely, less attention has been paid to the role of learning based on experience and non-science-based sources of knowledge –also known as doing, using and interacting (DUI) mode (Jensen et al., 2007). This kind of learning process is particularly relevant in: i) non R&D-performer firms, ii) firms with a lower degree of novelty and formality of their innovation efforts, iii) low and medium technological intensity industries and iv) small and medium size firms (Hirsch-Kreinsen, 2015).

Following this line, some scholars have claimed the importance of complementing indicators on R&D labs with others that account for different ways of developing innovative activities and building capabilities (Bender and Laestadius, 2005; Hirsch-Kreinsen, 2008; Rammer et al., 2009; Santamaría et al., 2009; Santarelli and Sterlacchini, 1990, among others). This claim is supported by the fact that non-R&D performing innovators represent a high proportion of firms in most countries –e.g. this involves half of European innovative firms (Arundel et al., 2007; Rammer et al., 2009; Thomä, 2017). This is also true for Latin American firms (e.g.: Dutrenit and Katz, 2005; Lugones and Suarez, 2010; RICyT, 2000; Yoguel and Boscherini, 1996) and it is what motivates this article.

We propose that besides R&D and non-R&D performers there is a set of heterogeneous firms carrying out other types of innovation efforts that are also innovators. We explore firms' innovative behavior profiles that account for different situations beyond having or not R&D labs. Following Thomä (2017), the patterns of knowledge creation that lies behind the behavior of non-R&D innovative firms are still a "black box" that needs to be investigated. Innovation activities performed outside R&D labs -quality assurance, continuous improvement systems, human resources training, and work organization- are relevant activities to fully comprehend firms' innovative efforts along with their innovative performance (Arundel et al., 2007).

In order to contribute to opening this black box, this article identifies a gradient of intermediate situations between formal R&D and the absence of innovative efforts. We claim that innovative efforts beyond formal R&D could be equally likely to trigger virtuous innovation processes. We study which types of firms' skills and capabilities besides STI learning explain their innovation profile. Our theoretical approach assumes that the development of capabilities is the consequence of a path dependent, accumulative and multidimensional learning process associated with knowledge accumulation, routines, organizational practices, interactive learning processes and linkages with the institutions from the national innovation system (Jensen et al., 2007; Nelson and Winter, 1982). Hence, we propose that the innovation profile is the consequence of the development of these dimensions. Then we also analyse to what extent firms' profiles are associated with their performance, in terms of innovative results.

The empirical analysis draws on a database with information about almost 4000 Argentine manufacturing firms for the period 2014-2016. The data comes from the second wave of the "National Survey on Innovation and Employment" (in Spanish Encuesta Nacional de Innovación y Empleo, hereinafter ENDEI II) carried out by the Ministry of Science and Technology and the Ministry of Labour. In order to analyse the relation between firms' capabilities and innovation profiles, multinomial logistic models were estimated. Results suggest that a high threshold of capabilities is necessary to overcome in order to start performing informal R&D activities. Then, probit and tobit models were estimated to explore the relation between innovation profiles and innovation results. Results suggest that more complex innovation profiles require higher levels of capabilities. Performing R&D activities is not just a matter of overcoming funding or appropriability failures but to accumulate skills and knowledge to set up a path of innovation based on the development of new knowledge and experimental development. Likewise, results show that while informal R&D is a critical threshold to increase the probability of obtaining product, process, organization and marketing innovations, formal R&D is key to get patents and to increase the share of new products on total sales.

The rest of the article is organized as follows: section two presents literature review on the role of R&D and other innovation activities in the process of innovation. The hypotheses are defined in section three. Section four presents the database, descriptive statistics and the methodology. The fifth section presents and analyse the results. Finally, some conclusions are drawn in section six.

2. Literature Review on The Role of R&D and Other Innovation Activities in the Process of Innovation

Within Evolutionary theory of innovation there is broad consensus that capability building is a cumulative and multidimensional process that arise from multiple activities that are not only reduced to R&D labs (Freeman, 1974; Nelson and Winter, 1982; Pavitt, 1984; Rosenberg, 1982). Under this framework, Nelson and Winter (1982) claim that innovation can be the result of either standardised processes of searching for improvements (routines to innovate) or the consequence of the identification of solutions to problems that appear in the daily operations of firms (innovation in routines). This latter way of innovation acquires more tacit features, requires the cooperation of agents widespread in different areas of the organisation, and complements formal R&D activities performed by firms. Similar appreciations can be found within Cohen and Levinthal (1990) and Teece and Pisano (1994) contributions.

Based on this general framework, three streams of empirical analysis can be found, synthetized in Table 1. Firstly, those contributions focused on R&D as the only relevant input to explain firms' innovation and performance. Secondly, a set of contributions aiming to identify innovative strategies of firms to account for intra- and extra-industry heterogeneity. Thirdly, there is a relatively new literature which we have named "The Black box opened: beyond formal R&D". These studies have arisen as a critical response to the literature centred on R&D. They show that innovation processes emerge from multiple activities and that many innovative firms are non-R&D performers.

The first group *-1.Focus on R&D performing firms-*, accounts for the literature that takes R&D as the only determinant of innovation dynamic in terms of patents and/or new products and processes. For the empirical exercises, R&D is introduced as a binary (R&D performers versus non-R&D performers) or a continuous variable, the latter known as R&D intensity (R&D expenditure to sales). This literature includes two types of groups: studies aimed at explaining innovation (group 1.1) and a set of articles that also add the relationship between innovation and productivity (group 1.2) (see table 1 for the main contributions within each group).

The group *1.1.R&D and innovation* is compounded by is a set of articles that provide evidence about inputs and outputs of the innovation process. Among the inputs, R&D is introduced as an independent variable in different

TABLA 1

LITERATURE REVIEW

	Premises and hypotheses	**Independent variables**	**Dependent variables**	**Literature***
1. Focus on R&D performing firms				
1.1 R&D and innovation	- Innovation depends on R&D - Innovation can be “made” through in house-R&D or “bought” by contracting external R&D	R&D as a binary variable: performers vs. non-performers R&D intensity: R&D expenditure/ sales In house vs. external R&D	Innovation results: new products and processes Patents	Cassiman and Veugelers, (2006); Vega-Jurado et al, (2008); Romijn and Albaladejo, (2002); Caloghirou et al., (2004); Duchesneau et al., (1979); Reichstein and Salter, (2006); Becker and Dietz, 2004; Poldahl (2006) Becker and Dietz (2004); Huang and Hou (2019); Pegkas, Staikouras and Tsamadias (2019)
1.2 CDM-type	R&D as determinant of innovation and productivity depending on innovation	Market share Diversification of activities R&D intensity	Patents Innovation results Labour productivity	Crepon, Duget & Mairesse, (1998); see Lööf et al., (2017) for a review; Notten et al., (2017) ; Ben Khalifa (2023).
2. Innovative strategies				
2	Inter and intra industry heterogeneity explained by firms’ innovation strategies	Innovation efforts (mainly R&D and acquisition of machinery) Innovation results, Sources of information for innovation, Methods of protection	Innovation strategies. Innovation results	Clausen et al. (2011); Yurtseven and Tandoğan, (2012); Fraga et al.(2008); Srholec and Verspagen, (2012); Frenz and Lambert, (2009), see Suarez (2015) for a review
3. The Black box opened: beyond formal R&D				
3.1 DUI mode of learning	Many innovations are associated with experience-based knowledge, with or without R&D labs.	Innovation management and work organization: - Incentive schemes to innovate; - internal competition and cooperation; -Interdisciplinary workgroups; - Quality circles; - Autonomy	- Innovation results - Productivity	Thöma, (2017); Rammer et al, (2009); Kirner et al (2009); Jensen et al, (2007); Som, (2012); Kirner et al. (2009); Som and Kirner (2015); Lundvall (2006), Malerba and Orsenigo (1997); Hervas-Oliver and Sampere-Ripoll, (2012) ; Fan, Huang and Xiong (2023) .
3.2 R&D and non-R&D based activities	Many innovations derive from innovation expenditures on non-R&D activities.	R&D, Use of advanced machinery, Design, Training, Skills intensity,	- Innovation results - Propensity to patent - Methods of innovating: R&D in-house, external R&D, creative non-R&D innovators, technology adopters - Non-R&D expenditures/ total innovation expenditures	Santamaria et al, (2009); Arundel et al, (2007); Huang et al, (2011); Bender, (2006). Santarelli and Starlaccini, (1990); Bender and Laestadius, (2005); Hirsch-Kreinsen, (2008); Thu Tran and Santarelli (2013); Hirsch-Kreinsen et al (2005); Grimpe and Sofka (2008); Heidenreich (2009); Liu, Shan and Li (2023).

* Selected contributions.

ways: performers versus non-performers, R&D expenditures as a percentage of total sales, in-house versus external R&D. Articles about "make and buy" innovation are also included within this literature, to the extent that they are based on the idea that firms can "make innovation" through in-house R&D or "buy innovation" through contracting external R&D. Then, innovation results and patents are considered among the results. Results are conclusive: most of this literature finds a positive impact of R&D on innovation outcomes.

Regarding *1.2.CDM-type* literature, we include the seminal paper of Crepon, Douguet and Mairesse (1998) and articles that have followed their methodology. These papers explain firm's innovation process in three steps. The first one explains R&D intensity by means of firm's market share and diversification of activities. In a second step the estimation of R&D is used to explain innovation results and, finally, innovation results are considered in the estimation of productivity. Most of this literature arrives to similar findings: productivity is explained by patents and new product/process which in turn are explained by R&D.

The second stream of the literature aims to explain inter and intra industry heterogeneity in terms of innovation strategies (*2. Innovative strategies*). Literature about innovation persistence falls within this group. The underlying idea is that firms can pursuit innovation thought different means and with different capabilities. Accordingly, the type of innovation strategy depends on firm's decisions about how to face competition, where R&D can play a central or a marginal, and even not a role at all. Innovation strategies are defining through factor analysis and clusters methods that include input and output variables of the innovation process: efforts, results, sources of information for innovation, methods of protection, etc. Results within this literature show the existence and persistence of firm heterogeneity, which is only partially determined by industry characteristics and opportunities.

The third group is called "*3. The Black box opened: beyond formal R&D*" and it is at the centre of the theoretical motivation of this article. Studies within this group claim that innovation is the result of multiple factors that go beyond the activities developed within R&D labs, which include new combinations of routines and solutions achieved both inside and outside the firm. It is assumed that these complementary dimensions to R&D are not considered by traditional indicators because of the belief that innovations not based on R&D are not relevant. Contributions within this group claim that when the study of innovation is reduced to the analysis of formal R&D, only a fraction of the productive structure is studied, which is usually based on knowledge-intensive activities. This segment involves firms with high technological capabilities and innovation rates, both in developing and developed countries.

To illustrate the importance of this for the case of Latin America, it is worth mentioning some "traditional" statistics. In Argentina only 20,24% of the manufacturing firms had a R&D lab in 2016, which contrasts with the 71% that claimed having done innovation activities (MINCyT, 2017). In Brazil, while 28% of the manufacturing firms did some innovation activities during 2011, only 3.7% declared having done R&D activities on a continuous manner (PINTEC, 2016). In Chile, only 1.6% of firms stated having an R&D lab in 2012 against 27% that declared having innovated (EIE, 2014). In Uruguay, 7% of manufacturing firms declared having performed R&D activities between 2013-15, while more than 31% made efforts in innovation (ANII, 2015). In Mexico, while 3% of the manufacturing firms had R&D labs in 2016, 18% declared carrying on innovation activities (ESIDET-MBN, 2016). Summing up, there is a significant distance between firms that have declared having carried out any formal or continuous form of R&D and those that performed innovation activities. Therefore, to know what determines that distance is a matter of key importance to understand how to promote more complex innovative behaviors. As we shall demonstrate, the level of a multidimensional set of capabilities plays a key role in that explanation.

Studies from developed countries also suggest that a large and heterogeneous group of firms with different capabilities, innovation efforts and innovative dynamics which are not necessarily explained by formal R&D activities is ignored when R&D is assume as the only possible innovation strategy. In these cases, another type of resources and abilities account for their innovative capability that can, as well, compensate the absence of efforts in R&D (Hirsch-Kreinsen, 2008; Santarelli and Sterlacchini, 1990; Som et al., 2013).

Within group 3 we have identified two set of articles, one is focused on the doing, using and interacting (DUI) mode of learning (group 3.1.) and the other assumes a wider perspective of innovative efforts (group 3.2.). Empirical evidence comes from micro-data in both groups, but while in the former the indicators stem mainly from ad hoc surveys, the later uses the traditional indicators coming from the standardized innovation surveys.

Within the "*3.1.DUI mode of learning*" group, the key component for the explanation of firms' innovative dynamic and performance is the learning process involving the combination of tacit and codified knowledge. Given the non-linear nature of the processes of capability building, modes of learning centred on DUI are a necessary condition for the emergence of forms based on STI learning processes, associated mainly with formal R&D. Following Thomä (2017), innovation at the firm level can occur with or without R&D activities, but rarely without DUI mode competencies acquired through informal processes of learning and experience-based know-how. An overly-strong focus on promoting only formal processes of in-house R&D thus ignores the fact that DUI mode competencies are a general prerequisite for successful innovation"

(Thoma, 2017: p. 1336).

The final row of the Table 1 includes a group of studies that start from the premise that both R&D and non- R&D- based activities lead to innovation results. Thus, all innovative efforts collected by the usual innovation surveys are included in the explanation of innovation. According to this literature, mainly in low and medium-low tech industries, innovation is the result of a particular configuration of tacit and codified resources developed by firms along their path dependence, rather than on their innovation strategies based in R&D. These articles have in common that, besides R&D, the other innovation efforts also played a key role: training, design, use of machinery and advanced technology, consultancy and contracting highly qualified personnel.

This paper aims to contribute to the summarized literature in a transversal way. We recognize the importance of formal R&D in carrying out innovations and improving firms' innovative performance (group 1). At the same time, we acknowledge the relevance of understanding heterogeneous situations (a gradient) between R&D performing firms and firms that do not invest in innovation (group 2). Then, we aim to break with the dichotomy of R&D versus non-R&D performing (group 3) by means of providing empirical evidence to explain alternative situations.

3. Hypotheses

We propose to study the *"innovation profile"* of firms as a gradient that includes firms that do not carry out innovation efforts, firms that do perform innovation efforts but without caring out R&D activities, firms that perform informal R&D, and firms that perform formal R&D within labs exclusively dedicated to those activities. This gradient is ordered in the sense that R&D performer firms are those with the most complex profiles. This assumption is based on the literature summarized under group 1 meaning that we do not neglect the importance of R&D activities in developing knowledge capable of being translated into sophisticated innovations. However, and in connection with the literature summarized in group 3, other ways of learning –besides R&D- are usually a prerequisite to those more complex ways of innovating. Thus, we claim that each one of the positions reached by firms in the gradient depend on the level of capabilities cumulated by firms along their path. Then, we claim that the greater the complexity of the firms' innovation profile, the better their innovative performance.

Therefore, our first hypothesis is that *the level of complexity of the innovation profile is associated with the accumulation of capabilities* (H1). We expect to find a positive relationship between profiles and the multiple dimensions of capabilities. We understand accumulation of capabilities as the aggregation of productive, absorptive (accumulated and potential), organisational and linkages dimensions (see Table 1, Appendix). H1 means that the cumulative process of capability development will show a positive relationship with the firm's profile. Then, the greater the accumulation of capabilities (in the five dimensions), the higher the probability of firms of having a formal R&D-based profile. This way, and similarly with the literature summarized in group 3, we assume that the search for technological and organisational improvements is an interactive process, that can begin in different areas of firms and simultaneously triggers similar processes in other ones (Kline and Rosenberg, 1989).

In a second step, we analyse the relationship between *firms' innovation profile and innovation results*. According to the literature discussed in section 2, multiple explanatory factors must be considered to understand the impacts of innovation activities that go beyond formal R&D. We start from the premise that among the group of firms non-performing R&D there are heterogeneous behaviours in terms of innovation results[1]. More specifically, we claim that not only formalised R&D profiles might have a positive correlation with innovation results, but also informal R&D profiles could be important to explain virtuous dynamics. In the same way, innovation efforts beyond R&D also constitute a differential element to explain the innovation outcomes.

Thus, our second hypothesis (H2) states that firms' innovation profile is positively associated to its innovation results. This hypothesis is based on the three streams of the literature reviewed in section 2. The first group provides empirical evidence about the positive impact of formal R&D on innovation results. Group 2 establishes a positive relationship between different combinations of innovation efforts and types of results. Finally, group 3 finds evidence on the association between firms' innovation efforts not focused on formal R&D and innovation results.

4. Data and empirical specification

4.1 Imperfect Competition

The database arises from the second wave of the "National Survey on Innovation and Employment" (in Spanish Encuesta Nacional de Innovación y

[1] Hypotheses proposed in this paper are focused on innovation results and not on economeic performance. The available information does not allow testing the relation between firms' R&D profile and productivity because of the existence of endogeneity. The source of this endogeneity is the simultaneity between R&D profile and economic performance because the variables were surveyed for the same period of time. On the contrary, innovation results refer to the period immediately after firms carried out their innovation efforts.

Empleo, hereinafter ENDEI II), which is a survey similar to the European CIS and based on the Oslo Manual recommendations. It consists of almost 4000 Argentine manufacturing firms with more than 10 employees for the period 2014-16.

Similarly to Arundel et al (2007)[2], a categorical variable was built for the analysis of innovation profiles. It assumes four different possibilities: 0 if the firm does not perform any innovation effort (without IE), 1 for firms that perform any innovation effort but do not carry out R&D (IE without R&D), 2 for firms that perform R&D but do not have a formal area dedicated to those activities (informal R&D), and 3 for firms with an R&D lab (formal R&D).

To characterise firm's capabilities, five dimensions were considered: productive, absorptive (accumulated and potential), connectivity, and lastly, organisational dimension. These dimensions are composed by a set of indicators, summarised in the Table 1 of the Appendix. To integrate these indicators, principal component methodology was used, in order to have an estimation of the latent variable associated to the different proposed aspects since selected variables for each one of the dimensions are assumed to be correlated (and the reviewed literature supports that). The first component for each capability dimension was selected (correlated with the largest eigenvalue of the variance and covariance matrix). The use of this methodology is based on the idea that the explanatory factors of each capability dimension are systemic and complementary. In this regard, each factor's aggregation produces synergy at an aggregated level (Laursen and Foss, 2003). It is worth indicating that the five identified dimensions respond to a conceptual segmentation of the different aspects of the firm that, in practice, are intimately related. The contribution of this article lies in the methodological separation that allows observing different relations between these capabilities and the R&D profiles.

There is a long trajectory among evolutionary studies regarding the importance of each selected dimension of capabilities. Productive capabilities derive from Nelson and Winter's (1982) ideas of productive process improvements which result from the identification and resolution of problems that emerge from the firm´s regular operations. They are identified, among other dimensions, from quality assurance and continuous improvement systems which are assumed to allow the firm to improve its routines. These methods account for the accumulation and building of capabilities, as long as they require codification and integration of tacit knowledge that is generated within the framework of the firm´s daily operations (Bessant et al., 2001; Jensen et al., 2007).

The concept of absorptive capacity has a long trajectory in the literature. Cohen and Levinthal (1990) define it as the firm's ability to recognize the value

2 They have identified four methods of innovating: in-house R&D performers, contract R&D, creative non-R&D innovators, technology adopters (machinery acquisition).

of new information, assimilate it, and apply it to commercial ends. Firms need qualified human resources in order to successfully integrate complex technological knowledge. Absorptive capacities are usually estimated from the stock of qualified human resources, and the existence of personnel assigned to innovation activities. We consider that the stock of qualified human resources accounts for the accumulated absorptive capabilities at a particular moment (accumulated absorptive capabilities). We exclude measuring absorptive capacities based on personnel assigned to innovation activities given the fact that R&D activities are the variables we will analyse. We additionally include the possibility that an improvement on innovation profiles can be the result of systematic efforts in training. This means acknowledging that the firm's capabilities also relate to the management of learning processes (potential absorptive capabilities).

The analysis of organisational capabilities has been approached from the identification of post-taylorist or post-fordist ways of work organisation. These are flexible and dynamic ways of organizing the productive and commercial process, and are found to be associated with the presence of areas specialised in human resources' management and the search for systematic mechanisms of knowledge generation and circulation within the organisation (Jansen et al., 2005; Lundvall, 2006; Roitter et al., 2013). Empirical analyses of the role of the post-fordist organisational work practices show that these favour the development of innovation results and capabilities (e.g.: Escribá Carda et al., 2013; Laursen and Foss, 2003; Shipton et al., 2006).

Connectivity capabilities address the linkages of the firm with its environment. Once again following Nelson and Winter's (1982), firms modify and shape their environment as well as their environment modify and shapes them. In addition, as it is proposed by Cohen and Levinthal (1990), there is information and knowledge outside the firm that it can incorporate and acquire, but in order to do that the firm must have the needed skills to identify knowledge, agents and institutions relevant to the firm and to speak the same language (Barletta, Robert y Yoguel, 2011). These linkages usually configure knowledge networks, then it is important to also understand the reasons of the linkages (to train the personnel, to develop a need product, consultancy for R&D activities, among others).

Finally, a set of variables to account for innovation results were selected. Four different types of results of the innovation process were analysed: i) new products or/and processes, ii) marketing and/or organizational changes, iii) patents and iv) the ratio of new product sales to total sales. These are the usual variables to test results. The third variable (patents) accounts for the most radical form of innovation. Although the critics it has received as a measure of innovation results, there is still plenty evidence about the importance of patents as a key asset of firms (Griliches, 2007). The last variable accounts, to some extent, for innovation results and firms' market performance, in the sense that new products are expected to provide the firm with quasi-rents in the Schumpeterian sense.

4.2 Empirical Strategy

The relationship between capabilities and innovation profiles is estimated using a multinomial logistic model, given the non-ordinal nature of the dependent variable. In this type of models, a set of equations is proposed, and each profile is explained by a set of observable characteristics of the firm. Specifically, if *Cap* is defined as a matrix of nx5 dimension composed by the five capabilities dimensions of the firm, and if we define *Ctrol*, as a matrix of nxk dimension where each k-vector includes a control variable; the i firm's conditional probability to choose R&D profile j is:

$$p_{ij} = \Pr\left[y_i = j \mid \mathrm{Cap}, \mathrm{Ctrol}\right] = \frac{\exp\left(\beta_{cap}\mathrm{Cap}_{ij} + \beta_{ctrl}\mathrm{Ctrol}_{ij}\right)}{\sum_0^3 \exp\left(\beta_{cap}\mathrm{Cap}_{ij} + \beta_{ctrl}\mathrm{Ctrol}_{ij}\right)}, j = 0,1,2,3$$

Where β_{cap} captures the statistical association between each capability dimension and the category of the R&D profile taken as a reference. In turn, β_{ctrl} captures the effect of control variables (size, industry, FDI, exporting condition and capital goods investments).

To analyse the relationship between these R&D profiles and innovation results, the following model has been estimated:

$$IR_i = \alpha_0 + \alpha_1 ID_{ij} + \alpha_2 Ctrol_i + \epsilon_i$$

Where the innovation results of the firm i, *IRi*, is measured in terms of: i) new products or/and processes, ii) new marketing and/or organizational processes, iii) patents and iv) the ratio of new product sales over total sales. In turn, firms' innovation results depend on the innovation profile and a group of control variables. Given the statistical distribution of each dependent variable, Probit models were estimated for the first three indicators and a Tobit model for the last one. In Table 2 of the Appendix, the variables used in the econometric exercises are synthetized.

A clarification is in order before moving forward. Given the nature of the database, the results should be read with caution as it is not strictly possible to establish the direction of causality (from capabilities to profiles or from profiles to capabilities, for example). The literature and previous evidence reviewed in section 2 suggest that there is strong causality between the variables we selected, but the results of the model cannot be read along these lines. While there are techniques to address the endogeneity mentioned above, such as the use of instrumental variables or the CDM models mentioned above, they have limitations. The identification of instrumental variables is problematic in itself, and they smooth out the existence of micro-heterogeneity, while it is not possible to ensure that they are unrelated to the dependent variable. CDM models require thinking of the innovation process as a linear dynamic of a succession of stages, which we discussed earlier in this paper. Therefore, the model will be estimated in the detailed version, even with the endogeneity constraints. The reading should always be done in terms of the relationship between variables (either positive or negative), and never in the sense of causality.

4.2 Descriptive Statistics

As shown in Table 2, the proportion of firms decreases as the innovation profile becomes more complex. In terms of size distribution, while smaller firms –less than 100 employees- tend to concentrate in less complex profiles (without IE and IE without R&D), larger firms -100 or more employees- are concentrated in more complex ones (formal and informal R&D). Only 6% of firms have foreign direct investments (FDI), a proportion that increases to 14% in the group of formal R&D, is 4% in the groups of firms with informal R&D, 8,16% in the group IE without R&D, and accounts for 4% for non-IE performers. Finally, from an industry perspective, firms from more technological intensive industries are overrepresented in informal and formal R&D groups.

Table 3 compiles the innovation results indicators according to R&D profiles. All the indicators considered tend to increase as the innovation profile becomes more complex. An interesting result for these statistics is that a relevant share of firms categorized as informal R&D has implemented new products or/and processes, although to a lesser extent than the ones labelled as formal R&D.

TABLA 2

DESCRIPTIVE STATISTICS

	Without IE	**IE without R&D**	**Informal R&D**	**Formal R&D**	**Total**
% of firms	35,10%	23,85%	25,85%	15,20%	100%
<100 employees	37,22%	23,85%	25,78%	13,16%	100%
>=100 employees	16,33%	23,80%	26,54%	33,34%	100%
% of firms with FDI	4%	8,16%	4,37%	14,30%	6,65%
Main industries	Food	Food	Other metal products	Chemical products	
	Textiles and wearing apparel	Textiles and wearing apparel	Food	Other metal products	
	Other metal products	Other metal products	Rubber and plastics products	Food	
	Printing	Rubber and plastics products	Furniture	Electrical machinery and apparatus	
		Leather	Machine-tools	Rubber and plastics products	
				Pharmaceuticals	

Source: Own elaboration based on ENDEI II. Weighted values.

TABLA 3

R&D PROFILE ACCORDING TO INNOVATION RESULTS

	IE without R&D	Informal R&D	Formal R&D	Total
New products or/and processes (% of firms)	54,68%	87,10%	88,3 2%	75,47%
Innovation in marketing or/and organization (% of firms)	36,53%	49,36%	62,3 5%	47,69%
Patents (% of firms)	5,83%	12,35%	16,4 7%	10,93%
New product sales/ Total sales	13,68%	14,74%	15,8 3%	14,7%

Source: Own elaboration based on ENDEI II. Weighted values.

5. Results

5.1 Relationship Between Innovation Profiles and Capabilities

Results confirm H1. Table 4 presents all results relative to the base category "without IE". Findings show that the four of the five capability dimensions are positively associated to the probabilities of different profiles of R&D. Furthermore, the coefficients justify the pertinence of the R&D profiles, given the different relationships between capabilities and pertaining to a R&D profile. Results of the multinomial logistic model suggest that productive, organisational and connectivity capabilities are the main differential elements between firms with less complex profiles (without IE versus IE without R&D) (column I)[3]. The estimated probability coefficient (i.e.: the relative risk ratio) is strongly higher in the first dimension of capabilities compared to the other two. In particular, the model suggests that being the structural characteristics equal, as connectivity capabilities increase, the probability that firms carry on efforts in innovation but not R&D is a 64% higher in relation to the possibility of not carrying on any effort. This probability decreases to 17% in the case of productivity capabilities and to 10% for organisational ones. In simpler words, this implies that in order to "start moving forward" into more complexes innovation profiles, firm must have accumulated capabilities regarding quality management, work organization and networking with institutions from de innovation system.

Once the "entry threshold" is overcome, related to a minimum level of productive, organisational and connectivity capabilities, the model shows that the capabilities needed to move towards the group of informal R&D firms are associated to four of the five dimensions considered: productive, accumulated absorptive, organisational and connectivity (column II). More precisely, the ratio of probabilities in relation to firms that perform IE but not R&D indicates that the probabilities that a firm to perform informal R&D are 9%, 11% and 13% higher in response to increases in organisational, accumulated absorptive, and connectivity capabilities respectively, and boost a 28% when productive capabilities overcome the median level of the database.

Finally, the probability that a firm had internalised R&D activities through the creation of a formal department (in relation to the probability of performing informal R&D) is positively correlated with productive and connectivity capacities, with a much higher influence of quality management level (column III). This is to say, reaching the informal R&D profile is already related with a change in the level of capabilities. In particular, higher productive capabilities are required, and to a lesser extent connectivity ones.

[3] The complete results are presented in Table 3 of the appendix.

TABLA 4

DIMENSIONS OF CAPABILITIES AND R&D PROFILES

	Total firms		
	Without IE to EI without R&D	**EI without R&D to informal R&D**	**Informal R&D to formal R&D**
	(I)	**(II)**	**(III)**
Potential absorption			
Productive	(+1.17)***	(+1.28)***	(+1.19)***
Organisational	(+1.10)***	(+1.09)**	
Accumulated absorption		(+1.11)*	
Connectivity	(+1.64)***	(+1.13)***	(+1.10)***
Control variables			
Industry dummies	YES	YES	YES
Size dummies	YES	YES	YES
FDI		***	***
Exports	***	**	***
Capital goods	NO	***	
Number of obs.	2539	2539	2539

Note: *, **, and *** indicate significance at 10%, 5%, 1% respectively. In brackets: risk ratio concerning the multinomial logistic model. Source: own elaboration based on ENDEI II.

In relation to the literature, outcomes points, on the one hand, to the systemic nature of innovation in terms of innovation activities and disseminated knowledge all along the organisation. In terms of Nelson and Winter (1982) firms need to develop different type of capabilities to improve routines, identify newer ones and, especially, successfully confront the process of competition. A firm that has not performed innovation activities and then radically moves into formal R&D processes would require drastic changes in its productive, organisational, and innovative activities in general. It would also require have accumulated dynamic capabilities, that would have pointed to the need to set a new strategy, and the development of ordinary capabilities, to lead it forward (Nelson, 1991). Innovation is the outcome not only of investments performed by the firms in the development of products, processes and organisational practices, but also of the construction of capabilities to progress and move forward with such a projects, which also requires the firm to link with the different institutions and agents from de innovation system (e.g.: Cohen and Levinthal, 1990; Teece and Pisano, 1994).

On the other hand, and assuming that R&D activities are a good proxy of more complex innovation projects, results show the relevance of studying less formalised innovation processes, as is the case of firms that carry out informal R&D. The sudden leap in terms of capabilities is produced precisely between firms that do and do not perform R&D (regardless the level of formalization). Moving towards less formalised R&D schemes represents a great improvement upon skill levels, knowledge, and competences. This matches the aforementioned literature according to which R&D only captures a small part of innovative processes, usually associated with high technological intensity firms as well as larger in size. In contrast, an important proportion of firms bases its innovative activity on less formal investments and even quite distinct from R&D, but equally relevant for its economic performance (e.g: Santarelli and Sterlacchini, 1990; Som et al., 2013).

Finally, it is worth to mention the relevance of accumulated over potential absorption to move towards a profile of greater complexity in terms of innovation activities. Even when potential absorption capabilities are demonstrated to be relevant to carry out innovation efforts, and obtain innovation results, they are not required for firms to change of innovation profile. In this regard, productive and connectivity capabilities are the most required ones to move to more complex innovation profiles.

5.2 Relationship Between R&D Profile and Innovation Results

Results regarding the relationship between R&D profile and firm´s innovation results are presented in Table 5. These estimations were run for a smaller number of firms given that firms that did not perform innovation efforts were not surveyed about results. Thus, the first category of innovation profile was drop from the analysis (without IE). According to the binary definition of the dependent variables three probit models were estimated, one for each one of the dependent variables: i) product and/ or process innovators; ii) marketing and/ or organization innovators and, iii) patents. In addition, a tobit model was estimated for the weight of new products in total sales, which ranges from 0 to 100.

Results of the estimation of new products and/or processes show that the passage from EI without R&D to informal R&D increases the probability of obtaining innovation results by 12%. On the contrary, moving from informal to formal R&D is not significant, meaning that pertaining to the formal R&D group is not correlated to higher probabilities of obtaining new processes or products, compared to the ones that carry out informal R&D.

Secondly, first column of Model II shows that moving from EI without R&D to informal R&D increases the probability to generate innovations in marketing and organization in 8,2%. In addition, different from the above case, moving from informal to formal R&D is significantly and positively associated to the probability of developing organizational or marketing innovations, which reaches 11,6% (column 2 of Model II). Thirdly, Model III shows that moving from informal to formal R&D significantly increases the probability of obtaining patents (+9,5%). Thus, results show that while informal R&D is a critical threshold to increase the probability of obtaining product, process, organization and marketing innovations, formal R&D is key to get patents. This result is consistent with the higher complexity of the profiles in terms of the possible outcomes of the innovation process, and to the descriptive statistics analyzed in section 4.3.

Finally, Model IV shows that the weight of new products on total sales increases when R&D profile becomes formal, and is not significant in the passage from EI without R&D to informal R&D.

All in all, hypothesis 2 is supported by results.

TABLA 5

R&D PROFILES AND INNOVATION RESULTS

	New products and/or processes (I) PROBIT		Marketing and organizational changes (II) PROBIT		Patents (III) PROBIT		% of new products on total sales (IV) TOBIT	
Base category	**IE without R&D**	**Informal R&D**	**IE without R&D**	**Informal R&D**	**IE without R&D**	**Informal R&D**	**IE without R&D**	**Informal R&D**
Informal R&D	0.121***		0.0823***		0.0306**		3.0136	
	(0.0195)		(0.0266)		(0.0128)		(2.2334)	
Formal R&D	0.143***	0.0219	0.198***	0.116***	0.125***	0.0946***	5.839***	2.825***
	(0.0198)	(0.0154)	(0.0280)	(0.0268)	(0.0173)	(0.0183)	(2.3201)	(1.3355)
FDI	0.0265	0.0265	-0.0576	-0.0576	-0.0508***	-0.0508***	2.6642	2.6642
	(0.0226)	(0.0226)	(0.0361)	(0.0361)	(0.0174)	(0.0174)	(1.7030)	(1.7030)
Industry	YES	YES	YES	YES	YES	YES	YES	YES
Size	YES	YES	YES	YES	YES	YES	YES	YES
Number of obs.	2054	2054	2054	2054	2598	2598	2207	2207

Note: *, ** and ***indicate significance at 10%, 5% y 1% respectively. In models I, II, and III marginal effects are reported. Standard errors in parentheses. Source: Own elaboration based on ENDEI II.

6. Conclusion

This article analysed the relationship between the level of firms' capabilities, innovation profiles and innovation results. H1 stated that the level of complexity of the R&D profile is associated with the accumulation of productive, absorptive, connectivity and organizational capabilities. H2 proposed that innovation results -in terms of new products or processes, new forms of marketing and organization, patents and the share of new product sales on total firms' sales- increase with the complexity of R&D profile.

Results of the empirical exercise suggest that performing formal R&D is positively associated with the existence of greater productive and connectivity capabilities. Moreover, greater capabilities are required in all the dimensions proposed -except for potential absorptive- for firms performing informal R&D in relation to firms performing innovation efforts without R&D. Thus, results support H1 and provide an approximation to the idea of a threshold of capabilities firms have to overcome in order to start doing informal R&D activities –and not just a funding-related market failure.

Similarly, results also confirm hypothesis 2. They highlight that the development of both formal and informal R&D activities is associated with higher probabilities of obtaining innovations. However, some differences are found depending on the considered dependent variable. Informal R&D seems to be a necessary threshold for the introduction of new product, process, marketing, and organization innovations and patents. Formal R&D performing firms have higher probabilities of obtaining patents, marketing and organization innovations, as well as for the share of new products on total sales.

These results contribute to the debate on the scope of public policy actions aimed at promoting R&D activities. On the one hand, they account for the importance of acting on different dimensions of capabilities as a mean to promote more complex R&D processes. On the second, results show the need to account for the micro-heterogeneity and differentiate policy actions according to the firm's level of capabilities. Therefore, the results of this paper suggest that non-R&D innovators should be considered within the innovation policy target in order to avoid the policy bias towards STI based innovation in high technological intensity industries. Thus, it is relevant to think about innovation policies in a wider sense, so that it addresses firm's restrictions to innovate in terms of the different levels of capabilities.

Regarding the literature, our results show the importance of acknowledging micro-heterogeneity and the non-linearity of the innovation process. Even though they re-confirm the importance of R&D formal activities in terms of innovation results, they also showed the relevance of other ways of performing innovation efforts, that could be equally important for the firm. At the same time, the association between R&D and capabilities call the attention on the relationship between causes and consequences. If R&D activities depend on the accumulation of capabilities, the low levels of R&D investments among firm's from developing countries is a symptom of low capabilities and it is not the cause of the underdevelopment of the productive structure (evidence at the country level seems to point that way – see Kim and Lee (2015)). In this respect, more research is required to shed light on the order of events between R&D activities and capabilities –which most probably co-evolve.

Finally, and connected to the last sentence, the limitations of this article are related to the nature of the available *cross-section* information, which restricts the possibility of analysing casual relationships and the estimation on leaps between R&D profiles and capabilities. In this respect, new survey waves will allow to approach these issues with panel analysis techniques, which will allow deepening the research on the relationship between capabilities, innovative processes, and innovation results of Argentine manufacturing firms.

References

ANII. (2015). Encuesta de actividades de innovación en la industria manufacturera y servicios seleccionados (2010-2012). Agencia Nacional de Investigación e innvoación, Uruguay.

Arundel, A., Bordoy, C., Kanerva, M. (2007). Neglected innovators: How do innovative firms that do not perform R&D innovate. Results of an analysis of the Innobarometer 9.

Barletta, F., Robert, V., & Yoguel, G. (2013). "Complementariedades de conocimiento, estrategias de conectividad e innovación en firmas industriales argentinas". *Revista de Economía Política de Buenos Aires*, (11), 32-Pages.

Becker, W., Dietz, J. (2004). "R&D cooperation and innovation activities of firms—evidence for the German manufacturing industry". *Research Policy*, 33, 209-223.

Ben Khalifa, A. (2023). "Impact of research and development (R&D) and information, and communication technology (ICT) on innovation and productivity evidence from Tunisian manufacturing firms". *Economics of Transition and Institutional Change*, 31(2), 341-361.

Bender, G. (2006). Peculiarities and Relevance of Non-Research-Intensive Industries in the Knowledge-Based Economy. Final Report of the Project "Policy and Innovation in Low-Tech –Knowledge Formation, Employment & Growth Contributions of the 'Old Economy' Industries in Europe – PILOT".

Bender, G., Laestadius, S. (2005). "Non-science based innovativeness. On capabilities relevant to generate profitable novelty". Fundacja Srodkowoeuropejskie Centrum Ekonomii Dzialania Spolecznego, Lublin, POLOGNE, p. 48.

Bessant, J., Caffyn, S., Gallagher, M. (2001). "An evolutionary model of continuous improvement behaviour". *Technovation*, 21, 67–77.

Caloghirou, Y., Kastelli, I., Tsakanikas, A. (2004). "Internal capabilities and external knowledge sources: complements or substitutes for innovative performance?" *Technovation*, 24, 29-39.

Cassiman, B., Veugelers, R. (2006). "In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition". *Management Science*, 52, 68-82.

Cohen, W., Levinthal, D. (1990). "Absorptive Capacity: A New Perspective on Learning and Innovation". *Administrative Science Quarterly*, 35, 128-152.

Crepon, B., Duguet, E., Mairesse, J. (1998). "Research, Innovation and Productivity: An econometric analysis at the firm level". *Economics of Innovation and New Technology*, 7, 115-158.

Dosi, G. (1988). "Sources, Procedures and Microeconomic Effects of Innovation". *Journal of Economic Literature*, 26, 1120-1171.

Duchesneau, T.D., Cohn, S.E., Dutton, J.E. (1979). "A study of innovation in manufacturing, determinants, processes and methodological issues". The Social Science Research Institute, University of Maine.

Dutrenit, G., Katz, J. (2005). "Innovation, growth and development in Latin-America: Stylized facts and a policy agenda". *Innovation: Management, Policy & Practice*, 7, 105-130.

EIE, 2014. 8va. Encuesta de Innovación en Empresas, 2011-2012. Principales Resultados. Ministerio de Economía, División de Innovación. Gobierno de Chile. Febrero, Chile.

Escribá Carda, N., Balbastre Benavent, F., Canet Giner, T. (2013). "Prácticas de recursos humanos y su impacto en los resultados de innovación: Una revisión teórica". *Ciencia y Sociedad*, 38.

ESIDET-MBN. (2012). Encuesta sobre Investigación y Desarrollo Tecnológico y Módulo sobre Actividades en Biotecnología y Nanotecnología. Instituto Nacional de Estadística y Geografía. Mexico.

Fan, M., Huang, W., & Xiong, S. (2023). "How enterprise interactions in innovation networks affect technological innovation performance: The role of technological innovation capacity and absorptive capacity". *Plos one*, 18(3), e0282540.

Fiorentin, Florencia, Mariano Pereira, y Diana Suarez. (2019). "Teoría y práctica de la política de innovación y el desarrollo de capacidades. Hechos estilizados del FONTAR". In *Ciencia y Tecnología para el Desarrollo*, editado por Gustavo Lugones y Fabián Britto. Bernal: UNQ.

Freeman, C. (1974). *The Economics of Industrial Innovation*. Penguin Books, Harmondsworth, Middlesex.

Griliches, Z. (2007). *R&D, Patents and Productivity*. University of Chicago Press, USA.

Grimpe, C., Sofka, W. (2009). "Search patterns and absorptive capacity: Low- and high-technology sectors in European countries". *Research Policy*, 38, 495-506.

Hall, B., Mairesse, J., Mohnen, P. (2010). *Measuring the Returns to R&D*. CIRANO-Scientific Publications 2010s-02.

Heidenreich, M. (2009). "Innovation patterns and location of European low- and medium-technology industries". *Research Policy*, 38, 483-494.

Hervas Oliver, J.L., Sempere Ripoll, F., Boronat Moll, C. (2012). "Process innovation objectives and management complementarities: patterns, drivers, co-adoption and performance effects". *UNU-MERIT Working Papers*, 2012-051.

Hirsch-Kreinsen, H. (2008). "Low -Technology: A Forgotten Sector in Innovation Policy". *Journal of technology management and innovation*, 3, 11-20.

Hirsch-Kreinsen, H. (2015). Innovation in low-tech industries: current conditions and future prospects. In *Low-tech innovation*. Springer, pp. 17-32.

Huang, C., Arundel, A., Hollanders, H. (2011). "How firms innovate: R&D, non-R&D, and technology adoption". Paper presented at the DIME Final Conference, 6-8 April 2011, Maastricht.

Huang, C. H., & Hou, T. C. T. (2019). "Innovation, research and development, and firm profitability in Taiwan: Causality and determinants". *International Review of Economics & Finance*, 59, 385-394.

Jansen, J.J.P., Van Sen Bosch, F.A.J., Volberda, H.W. (2005). "Managing potential and realized absorptive capacity: how do organizational antecedents matter?" *Academy of management journal*, 48, 999-1015.

Jensen, M.B., Johnson, B., Lorenz, E., Lundvall, B.Å. (2007). "Forms of knowledge and modes of innovation". *Research Polic*y, 36, 680-693.

Kim, Y.K., Lee, K. (2015). "Different Impacts of Scientific and Technological Knowledge on Economic Growth: Contrasting Science and Technology Policy in East Asia and Latin America". *Asian Economic Policy Review*, 10, 43-66.

Kirner, E., Kinkel, S., Jaeger, A. (2009). "Innovation paths and the innovation performance of low-technology firms—An empirical analysis of German industry". *Research Policy*, 38, 447-458.

Kline, S., Rosenberg, N. (1989). An Overview of Innovation. In: Landau, R., Rosenberg, N. (Eds.), *The Positive Sum Strategy: Harnessing Technology for Economic Growth*. National Academies Press, Washington.

Laursen, K., Foss, N.J. (2003). "New human resource management practices, complementarities and the impact on innovation performance". *Cambridge Journal of Economics*, 27, 243-263.

Liu, M., Shan, Y., & Li, Y. (2023). "Heterogeneous Partners, R&D cooperation and corporate innovation capability: Evidence from Chinese manufacturing firms". *Technology in Society*, 72, 102183.

Lugones, G., Suarez, D. (2010). "STI indicators for policy making in developing countries: An overview of experiences and lessons learned". UNCTAD Conference Room Paper, Multi-Year Expert Meeting on Enterprise development policies and capacity-building in science, technology and innovation Ginebra.

Lundvall, B.Å. (2006). "Knowledge Management in the Learning Economy". *DRUID Working Papers 06-06*, DRUID, Copenhagen Business School, Department of Industrial Economics and Strategy/Aalborg University, Department of Business Studies.

Malerba, F., Orsenigo, L., Peretto, P. (1997). "Persistence of innovative activities, sectoral patterns of innovation and international technological specialization". *International Journal of Industrial Organization*, 15, 801-826.

MINCyT. (2017). Encuesta Nacional de Dinámica del Empleo y la Innovación II (ENDEI 2014-2016). Ministerio de Ciencia, Tecnología e Innovación productiva/ Ministerio de Trabajo, Empleo y Seguridad Social, Buenos Aires, Argentina.

Nelson, R. (1991). "Why do firms differ, and how does it matter?" *Strategic Management Journal*, 12, 61-74.

Nelson, R., Winter, S. (1982). *An evolutionary theory of economic change*. The Belknap Press of Harvard University Press, Cambridge.

OECD. (2002). *Frascati Manual*. Proposed Standard Practise for Surveys on Research and Experimental Development.

OECD. (2005). *Oslo Manua*l. 3rd edition. Guidelines for collecting and interpreting innovation data. First edition 1992. OECD, Paris.

Oslo, M. (2018). "Guidelines for collecting, reporting, and using data on innovation: The measurement of scientific, technological and innovation activities". *Luxembourg: OECD Publishing, Paris: Eurostat*.

Pavitt, K. (1984). "Sectoral patterns of technical change: towards a taxonomy and a theory". *Research Policy*, 13, 343–373.

Pegkas, P., Staikouras, C., & Tsamadias, C. (2019). "Does research and development expenditure impact innovation? Evidence from the European Union countries". *Journal of Policy Modeling*, 41(5), 1005-1025.

PINTEC. (2016). Pesquisa de innovaçao, IBGE, Brasil. http://www.pintec.ibge.gov.br/.

Poldahl, A. (2006). "The two faces of R&D: Does firm absorptive capacity matter?" *Working paper Series*, n. 1. SE-701 82 Örebro, Sweden.

Rammer, C., Czarnitzki, D., Spielkamp, A. (2009). “Innovation success of non-R&D-performers: substituting technology by management in SMEs”. *Small Business Economics*, 33, 35-58.

Reichstein, T., Salter, A. (2006). “Investigating the sources of process innovation among UK manufacturing firms”. *Industrial and Corporate Change*, 15, 653-682.

RICyT. (2000). *Manual de Bogotá: Normalización de Indicadores de Innovación Tecnológica en América Latina y el Caribe*. OEA/ RICYT/COLCIENCIAS/OCT, Bogotá, Colombia.

Roitter, S., Erbes, A., Kababe, Y. (2013). Procesos de aprendizaje en el sector servicios: ¿Nuevas formas de organización del trabajo?, in: Suarez, D. (Ed.), *El Sistema Argentino de Innovación: instituciones, empresas y redes. El desafío de la creación y apropiación de conocimiento*. UNGS, Buenos Aires.

Romijn, H., Albaladejo, M. (2002). “Determinants of innovation capability in small electronics and software firms in southeast England”. *Research Policy*, 31, 1053-1067.

Rosenberg, N.e. (1982). *Inside the Black Box: Technology and Economics*. Cambridge University Press.

Santamaría, L., Nieto, M.J., Barge-Gil, A. (2009). “Beyond formal R&D: Taking advantage of other sources of innovation in low- and medium-technology industries”. *Research Policy*, 38, 507-517.

Santarelli, E., Sterlacchini, A. (1990). “Innovation, formal vs. informal R&D, and firm size: Some evidence from Italian manufacturing firms”. *Small Business Economics*, 2, 223-228.

Shipton, H., West, M.A., Dawson, J., Birdi, K., Patterson, M. (2006). “HRM as a predictor of innovation”. *Human Resource Management Journal*, 16: 13–27.

Som, O., Kirner, E. (2015). *Low-tech Innovation*. Springer International Publishing, Switzerland.

Som, O., Kirner, E., Jäger, A. (2013). “Absorptive capacity of non-R&D-intensive firms in the German manufacturing industry”. *35th DRUID Celebration Conference 2013*, Barcelona, Spain, June 17-19.

Teece, D., Pisano, G. (1994). “The Dynamic Capabilities of Firms: an Introduction”. *Industrial and Corporate Change*, 3, 537-556.

Thomä, J. (2017). “DUI mode learning and barriers to innovation—A case from Germany”. *Research Polic*y, 46, 1327-1339.

Thu Tran, H., Santarelli, E. (2013). “Determinants and Effects of Innovative Activities in Vietnam. A Firm-level Analysis”. *Quaderni - Working Paper DSE N°909*, University of Bologna, Department of Economics.

Vega-Jurado, J., Gutiérrez-Gracia, A., Fernández-de-Lucio, I., Manjarrés-Henríquez, L. (2008). “The effect of external and internal factors on firms’ product innovation". *Research Policy*, 37, 616-632.

Verspagen, B. (1995). "R&D and productivity: A broad cross-section cross-country look". *Journal of Productivity Analysis*, 6, 117-135.

Yoguel, G., Boscherini, F. (1996). "Algunas reflexiones sobre la medición de los procesos de innovación: la relevancia de los elementos informales e incrementales". *Revista Redes*, 3, 95-116.

Appendix

TABLA A1

DIMENSIONS AND VARIABLES USED FOR THE ANALYSIS OF PRINCIPAL COMPONENTS

Dimension	Variables	Measure Unit
I. Productive	Productive process´ critical characteristics specification	0 if it is not being used / 1 if it is being used (one binary variable for each type of activity)
	Traceability	
	Equipment for process improvement	
	Tools for systems of continuous improvement	
	Routines to orientate activities of design	
	Specific tools for project management	
II. Accumulated absorptive capacity	% of personnel with university degree to total employment	0 to 100 in percentage points (one continuous variable for each type of personnel)
	% of engineers to total personnel with university degree	
	% of personnel with technical qualification to total employment	
III. Potential absorptive capacity	Quantity of functions of the area responsible for organising training activities (diagnosis, planning, methodology design, definition of working hours, careers plans, and evaluation practices)	0 to 7
	Percentage of personnel trained at a hierarchical level	0 to 100 in percentage points (one continuous variable for each type of level)
	Percentage of personnel trained at a supervisor level	
	Percentage of personnel trained at a non-hierarchical level	
	Number of provided courses (management, organisation and enterprises direction/administration; strategic planning; scientific and technical update; commercial management of logistics and distribution; informatics)	0 to 7
IV. Organizational capacity.	Staff rotation	0 if they do not rotate / 1 if they do rotate
	Degree of personnel´s autonomy (response to problems at the workstation: calling the supervisor, solving and communicating the supervisor, solving without communicating , solving and documenting)	0 to 3
	Personnel involvement in HR activities (non-participation, efficiency evaluation, improvement plan and evaluation, self-evaluation and implementation of the new improvement suggestion, and so on)	0 to 3

V. Connectivity capacity	Set of binary variables for linkage with a firm, university, S&T public institution or a consultant.	0 if the firm was not linked / 1 if the firm was linked (one binary variable for each type of institution/agent, in total 4 variables)
	Set of binary variables for linkage to personnel training, R&D, test and trials, technological exchange, organisational changes or improvements, product or process development or improvements, industrial design or engineering activities	0 if the firm was not linked to the purpose / 1 if the firm was linked to the purpose (one binary variable for each type of purpose, in total 7 variables)

TABLA A2

VARIABLES USED IN THE ECONOMETRIC MODEL

Variable	Definition	Measure Unit
Innovation profile	Categorical variable that captures the innovative efforts (IE) of the firm	0 without IE / 1 IE without R&D / 2 informal R&D / 3 formal R&D
Firm´s Capabilities		
Productivity Capability	First principal component associated to the efforts in quality management.	Variable centred in 0 that takes values in all the range of possibilities.
Accumulated absorptive capacity	First principal component associated to the Human Resources qualification.	
Potential absorptive capacity	First principal component associated to the Human Resources training.	
Organisational Capability	First principal component associated with the work organisation.	
Connectivity capability	First principal component associated to links with different types of institution and with different objectives.	
Innovation results		
New products and processes	% of firms that introduced new products and/or processes in 2012	0 No/ 1 Yes
Marketing and organizational changes	% of firms that introduced marketing and/ or organizational changes in 2012	0 No/ 1 Yes
Patents	% of firms that patented in 2012	0 No/ 1 Yes
% of new products on total sales	Ratio between new products sales and total firms sales in 2012	Continuos variable that ranges between 0 and 100
Control Variables		
Size	Size according to employment level and sales (2010).	0 Small / 1 Medium / 2 Large
Industry	Industry classification according to ISIC Rev.3.1	
Origin of capital	Existence of FDI (2010-12)	0 No /1 Yes
Exports	Exports (2010-12)	0 does not export / 1 does export
Capital goods	Proportion of total expenditures allocated to buying equipment and machinery (2012)	From 0 to 100%

TABLA A3

RELATIONSHIP BETWEEN CAPABILITIES AND R&D PROFILES – MULTINOMIAL LOGISTIC REGRESSION

	Total firms		
	Without IE to EI without R&D	**EI without R&D to informal R&D**	**Informal R&D to formal R&D**
	(I)	**(II)**	**(III)**
Potential absorption	(+1.06)	(-0.94)	(+1.01)
Productive	(+1.17)***	(+1.28)***	(+1.19)***
Organisational	(+1.10)***	(+1.09)**	(-0.93)
Accumulated absorption	(+1.07)	(+1.12)*	(+1.10)
Connectivity	(+1.64)***	(+1.13)***	(+1.10)***
Control variables			
Industry dummies	YES	YES	YES
Size	YES	YES	YES
Medium	(+1.18)	(-0.96)	(+1.46)***
Large	(-0.88)	(-0.86)	(+1.82)***
FDI	(+1.18)	(+2.6)***	(-0.59)***
Exports	(+1.79)***	(+1.35)***	(+1.63)***
Capital goods	NO	(-0.99)	(+1.00)
Constant	(-0.91)	(+0.51)**	(-0.30)***
Number of obs	2539	2539	2539

Note: *, **, and *** indicate significance at 10%, 5%, 1% respectively. Risk ratio concerning the multinomial logistic model. Source: own elaboration based on ENDEI II.

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