Explaining differences in the returns to R&D in Argentina. The role of contextual factors

Valeria Arza[ab]*, Xavier Cirera[c], Emanuel López[b] and Agustina Colonna[b]

[a]National Research Council for Scientific and Technical Research (CONICET); [b]Research Centre for Transformation (CENIT), Economic and Business School, National University of San Martin (EEYN-UNSAM); [c]World Bank, Brazil Country Office; Firms, Innovation and Entrepreneurship Finance; Competitiveness and Innovation Global Practice

***corresponding author**
varza@unsam.edu.ar
+5491163763624
Av. Roque Sáenz Peña 832, 2do piso, Ciudad de Buenos Aires, Argentina

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Abstract

Argentinean firms' investments in R&D are well below its regional peers. One potential explanation for this fact is the existence of low and heterogeneous returns for these investments. This paper uses novel microdata to estimate the returns to R&D and analyse the role of contextual factors in shaping its heterogeneity. The findings confirm that returns are indeed heterogeneous and depend on some important factors related to the market context, such as measures of uncertainty; and the knowledge context, such as knowledge spillovers. Acknowledging that heterogeneity of returns depends on firms' context is crucial for designing innovation policies to boost private R&D returns.

Keywords: productivity; R&D; Argentina; knowledge context; market context

JEL codes: L25; O25; O33; O54

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1. Motivation

Investments in knowledge capital and other innovation related activities are considered a key enabling factor in the catching up process; both in terms of climbing the technological ladder and promoting the processes of reallocation and "creative destruction" (Schumpeter 1942; Griffith, Redding, and Reenen 2004). Since the early 1990s there has been a wide consensus in the economic literature on the link between investments in innovation, productivity and economic growth. Evidence on this link has been produced at a macro (e.g. Teixeira and Queirós 2016), sectoral (e.g. Strobel 2012) and micro (e.g. Crespi and Zuniga 2012) levels.

The creation of new knowledge involved in innovation is a cumulative process, and past performance has an important influence on firms' knowledge efforts and subsequent yields. In addition, heterogeneity could exist in the effectiveness in which investments in innovation are converted into productivity or sales growth – its returns (Fung 2004; Marín and Petralia 2018; Ngai and Samaniego 2011). For instance, consider wine production in Cuyo region, the traditional location for wine production in Argentina, compared to Patagonia region, where new ventures are emerging, and some experimentation is taking place. It is likely that one peso invested in research and development (R&D) may not enhance productivity equally in both regions since knowledge and infrastructure conditions, access to inputs, and the market context are different; creating distinct opportunities in complementing private efforts in R&D. In other words, knowledge investment is not univocally transmitted into performance.

Factors intervening both in the innovation *process* and/or in the *context* of innovation may affect returns. The former refers to the way firms deploy innovative projects internally and the latter to characteristics of the environment where the innovative investments take place (Hambrick and MacMillan 1985). We are particularly interested in understanding how contextual factors offer a different array of opportunities and constraints that shape the possibilities of making the most of internal innovation efforts. In other words, the aim of this paper is to analyse how context-based aspects hamper or boost firms' R&D returns. Identifying what factors help explaining this heterogeneity is critical for designing innovation policies that want to effectively incentivize R&D investments, since policies that aim at encouraging investments in R&D but cannot affect its returns will fail.

While traditionally the innovation systems (IS) literature (Lundvall 1992; Nelson 1993) has emphasised the systemic nature of innovation and the importance of key factors and institutions in promoting a learning environment that could contribute towards the development of firms' capabilities, there are other factors, outside the realm of Science, Technology and Innovation (STI) policies, that have an impact on the returns to investments in innovation. First of all, development economics scholars have argued that the quality of institutions, regulation and macroeconomic instability can largely explain the poor catching-up performance of developing countries (Cirera and Maloney 2017). Secondly, innovation scholars also identified some key contextual variables that affect innovation rents and decisions. On the one hand, demand-driven theory has emphasised the increase of market demand on certain outputs may orient innovation efforts towards particular directions (Schmookler 1962). On the other, from neoclassical economics, there have been emphasis on how market competition affects pre and post innovation rents (Aghion et al. 2005). Following these lines of research, we propose that contextual factors can be grouped in two main dimensions: factors that affect more directly knowledge accumulation - *knowledge contextual factors*; and factors that affect firms' incentives to allocate resources to innovation - *market contextual factors*.

The paper contributes to the literature conceptually, methodologically and empirically. Conceptually, we organise in those two dimensions (knowledge and market) the scattered approaches that highlight that heterogeneous returns to investment may be explained by contextual characteristics. Methodologically, we start from the knowledge production function approach pioneered by Griliches (1979) and expand it to include interactions between R&D and contextual variables to reflect heterogeneous returns of R&D. We operationalise the knowledge and market contexts through a set of variables defined at the sectoral or regional levels. Empirically, the paper contributes to the literature about the Argentinean IS, using a novel micro dataset to analyse a particularly relevant question for the country on how and to what extent contextual factors matter for innovation.

To advance the main results, the different estimates show that the returns are indeed heterogeneous, and that both knowledge and market context factors are significant to mould R&D returns. We find that spatial knowledge spillovers, measured through regional migration of highly educated workers, enhance R&D returns; while market uncertainty, measured through credit volatility at sectoral level, significantly reduces returns.

Argentina constitutes a well-suited case for exploring our question given the country's poor productivity growth performance over the last decade. In addition, Argentina underperforms peers such as Brazil or Chile in terms of the levels of privately funded innovation investments. The country also presents a broad diversity of contexts in its large territory. It encompasses a wide variety of climates and natural resources, has unequal distribution of income, population and human capital, and an industry composition that includes a large range of activities. The country has also suffered recurrent periods of high macroeconomic volatility and policy swings

(Arza and Brau 2021) that has pushed firms towards the use of defensive strategies to cope with uncertainty that often undermined longer-term innovative and productivity enhancing strategies (Katz 2000; Katz and Bernat 2011; Arza 2013; Kosacoff 2000; Chudnovsky 2001; Fanelli 2002). More importantly, over the last decade Argentina's innovation policies have experienced significant changes in its governance and objectives following successive changes in the government administration (Gurcanlar et al. 2021).

The remaining of this document is organized as follows. Section 2 presents the conceptual framework. Section 3 describes the Argentinean context and its R&D and productivity performance to motivate the discussion. Section 4 presents the methodology and data. Section 5 shows the results of the production function estimates and the role of contextual factors. Section 6 concludes offering some policy recommendations and lines for future research.

2. Conceptual framework

A large microeconomic literature has explored heterogeneity when it comes to firm performance in terms of productivity differences (Bartelsman, Haltiwanger, and Scarpetta 2013), export behaviour (Bernard and Jensen 1999) or productivity and technology diffusion (Andrews, Criscuolo, and Pilat 2015). This often reflects heterogeneities in managerial talent (Lucas 1978), learning (Jovanovic 1982) or abilities (Acemoglu et al. 2018). Regarding innovation investments, its relationship with firm performance has been extensively studied using the knowledge enlarged production function approach pioneered by Griliches (1979). With the expansion of the innovation surveys in the European Union, and later on in other countries, Crepon, Duguet, and Mairesse (1998) proposed a framework that models the interdependent relation between investment in R&D, innovative outputs and firms' productivity – the Crepon, Duguet and Mairesse (CDM) model. This has been estimated in several contexts, including developing countries.[1] Although this literature has created consensus on the relevance of investments in innovation in terms of firms' productivity and growth, there is less clarity about what factors affect the rate of return and how these differ across firms. Furthermore, while internal factors to the firm are key determinants of performance heterogeneity, it is also acknowledged that external factors play an important role (Syverson 2011).

The national IS literature (Lundvall 1992; Nelson 1993) for long has emphasised the need to strengthen the learning environment to support the development of firm's capability. One key element emphasized by this literature is that the connection between the firm and other actors in their production context matters as much as firms' internal efforts when assessing firm's innovative performance. These arguments were later also defined at regional (Cooke 2001;

[1] Examples of such studies are: Benavente (2006) applied an adapted version of the CDM framework using Chilean cross-section data, and found that neither R&D nor innovative results (share of innovative sales) have an effect on productivity (measured as value added per worker). Crespi and Zuniga (2012) applied the CDM framework on micro data for six Latin American countries. They find that greater investment in R&D leads to a higher probability of having at least one process or product innovation. Additionally, results show a positive impact of technological innovation on productivity (log of sales per employee) for all countries except Costa Rica. Moreover, they find that the magnitude of the results is very heterogeneous. Crespi, Tacsir, and Vargas (2016) used 2010 firm level data to analyze 17 Latin American countries. Results show that investment in R&D per worker increases the probability that the firm will innovate, and that this translated into a strong increase in labour productivity (measured as log of sales per employee). These results are robust to five different measures of innovation: innovation of product or process, product innovation, process innovation, innovative sales (share of sales of new products) and filing for intellectual property rights. In Argentina the CDM framework was first used by Chudnovsky, López, and Pupato (2004) and then by Arza and López (2010). Both papers showed that investment in R&D boosts firms' labour productivity.

Cooke, Uranga, and Etxebarria 1997) and sectoral (Malerba 2002) levels. Thus, according to this literature innovation policy should be concerned about nurturing an environment prone to learning, via supporting learning infrastructures and institutions promoting networks to make the most of knowledge complementarities. This is because innovation draws from previous accumulation of knowledge which is largely embodied in actors located in the context of innovation.

However, there are strands of literature that emphasised on other contextual aspects that are relevant for creating the type of incentives needed to encourage long-term investments. One of these aspects is institutional quality and its impact on growth, which has been part of the development policy agenda (World Bank 2020). The claim is that a poorly developed institutional and regulatory framework would undermine business confidence needed to commit to long-term investment and the capacity to anticipate future returns on investment (North 1990). Similarly, macroeconomic uncertainty has also been at the core of development economic studies for similar reasons: it makes more complex to anticipate the future behaviour of key variables and therefore creates disincentives for irreversible investments (Caballero and Pindyck 1996). This literature has dealt primarily with investment in capital goods, but the arguments can be still valid for investment in R&D. In addition, there are two other contextual aspects that have been previously studied in relation to innovation directly. One of them relates to demand-pull factors in guiding technological progress and innovation decisions particularly in certain sectors (Schmookler 1962). The other one is the concept of market competition and its effect on pre and post innovation rents (Aghion et al. 2005). Based on these ideas and relevant empirical literature we propose a conceptual framework that characterise the context of innovation considering two dimensions: knowledge contextual factors and market contextual factors. We argue that the knowledge environment affects the opportunities for firms to learn and to take advantage of knowledge created outside its boundaries, while traditional market environment features, such as competition, demand levels or the business climate, will affect incentives and the profitability of R&D projects. Both dimensions, simultaneously, shape the returns to R&D. [2]

Exploring the context: knowledge and market factors

We now review the literature identifying and highlighting different contextual characteristics belonging to each dimension considered, which is summarised in the boxes for knowledge and market context in Figure 1. This review will help us operationalise variables in the methodological section.

Knowledge contextual factors

There is a vast literature investigating the intrinsic characteristics of technological regimes, the supply of scientific knowledge, and other technology and innovation systemic factors. These contextual factors related to knowledge are normally measured at the *meso* (sector/region) level, considering that firms interact depending on their learning and technological capabilities (Teece and Pisano 2003).

[2] Maloney (2017) provided similar arguments regarding the need for innovation policy to complement the innovation system approach with other contribution from neoclassical economics, to capture often-underplayed barriers that prevents the accumulation and allocation of production factors other than knowledge and that could explain cross-country differences in innovation.

One important focus of the literature has considered the existence of *knowledge spillovers* driving firms' performance, i.e. factors defined at spatial or sectoral level that boost firms' learning capacity through their access to external knowledge. In the systemic approach, learning by interaction has a key role in allowing firms' access to external knowledge embodied in other organizations or individuals.

The role of *sectoral* spillovers has been highlighted by the literature of technological opportunities that argues that industry differences in the returns to R&D are explained by variations in the set of technological options achievable via R&D (Klevorick et al. 1995). Several sources can renew the pool of technological opportunities, such as the technological trajectories (Malerba and Orsenigo 1995; Pavitt 1984);[3] or policy supporting universities and research institutions that produce market-relevant scientific knowledge or by advancement in the industry. This has been assessed empirically in Klevorick et al. (1995) and other contributions include Marín and Petralia (2018), Fung (2004) or Kafouros and Buckley (2008).[4]

In addition, there is a role for *spatial* spillovers. This literature is motivated by the fact that innovation is not randomly distributed in the territory but tends to concentrate geographically

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[3] Pavitt (1984) classified industries according to the source of technology (e.g. inside/outside the firm, government/private-financed), users' needs (e.g. price/performance), and methods used to appropriate benefits from innovation (e.g. secrecy, patents, time lags, unique knowledge, etc.). Similarly, Malerba and Orsenigo (1995) explored the dynamics of technological change and defined two different groups, labelled technological regimes, which were characterized by a specific combination of conditions of technological opportunity, appropriability of innovation, cumulativeness, and properties of the knowledge base defined at the sectoral level.

[4] Another important related literature summarized in Griliches (1994) and more recently in Bloom et al. (2017) focus on the productivity of new ideas. This literature is more macro but has sector specific implications, since in some sectors ideas "are harder to get" and this will affect their returns to R&D investments to develop them.

(Audretsch 1998). Marshall (1890) identified three factors that explain geographical concentration: availability of skilled workers; availability of specific inputs (from natural resources to the existence of relevant scientific and technological public organizations); and technological spillovers.[5] Innovation studies have analysed the relevance of regional innovation systems, stressing how socio-economic factors that are present in the territory where the firm produces affect both the level and the effectiveness of their investment in R&D (Cooke et al. 2011; Crescenzi and Rodríguez-Pose 2013). The local institutional capacity, the supply of human capital (including labour mobility across geography), and public support for knowledge generation are all relevant factors for firms' productivity and innovativeness (Capello 2011; Felsenstein 2011). Local literature coming from Latin America (Llisterri and Pietrobelli 2011) and, in particular, Argentina (Niembro 2017; Yoguel, Borello, and Erbes 2009) stress the importance of the regional innovation systems' characteristics both for performance and innovation policy design.

Beyond spillovers, the literature extensively assesses the contribution of policies to enhance the production and use of scientific knowledge in the production sphere; either using policy tools designed to increase the likelihood of knowledge transfer (i.e. grants for research industry collaboration or consortia development) or affecting the supply of knowledge directly (i.e. research and university policies training programs, technical assistance through management and technology extension, financing infrastructure, etc.). STI policies have a key role in creating a *support to knowledge supply*, promoting a collective vision of what should be done and how to enhance innovation performance (Metcalfe and Ramlogan 2008; Soete, Verspagen, and Ter Weel 2010; Kline and Rosenberg 1986), which is likely to affect the returns to R&D.

[5] These elements gave birth to the new economic geography, and the study of economics of agglomeration, led by Krugman (1991).

But perhaps one of the most direct effects of STI policies on the rate of return of R&D comes from providing a supportive scientific system and infrastructure that promotes knowledge interactions between different actors and increases the innovation capabilities of firms.

Market contextual factors

We refer here to some well-studied market and institutional characteristics that may work as key *contextual market factors* affecting firms' returns to investments in innovation, which have been highlighted as important by various traditions of innovation scholars.

There is consensus about the simultaneous determination of *market competition* and innovation. The concepts of creative destruction and creative accumulation in Schumpeterian approaches are proof of an awareness of this simultaneity. In a regime characterised by creative destruction, entrepreneurs are driven by fear of others innovating first, and therefore the innovative base is continuously being enlarged by the entry of new innovators, increasing market competition. In a creative accumulation regime, on the other hand, it is monopoly power that encourages innovation, which in turn will be rewarded by monopoly rents, increasing market concentration.[6] Thus, market competition may affect both incentives to invest and opportunities to appropriate rewards from such investment, potentially resulting in a non-linear

[6] Many empirical studies have attempted to find economic mechanisms to explain what was considered a statistical regularity of a highly concentrated market structure in a highly R&D-intensive sector; since Scherer (1967) the relation between market competition was modelled in an inverted-U shape. However, since these variables are related in both directions the methodological challenge in empirical studies has been how to account for such endogeneity (e.g. Aghion et al. 2005; Davies and Lyons 1996; Sutton 1998)

relationship as in Aghion et al. (2005) and depending on existing technological rivalry and productivity gaps within sectors.

Lack of *demand* or uncertainty about future demand are often found in micro studies as deterrent barriers that prevent firms' decisions to innovate (e.g. García-Quevedo, Pellegrino, and Savona 2016). There is a long tradition in innovation studies highlighting the role of demand in pulling technological progress, often based on Kaldor's ideas about its importance in encouraging investment and the virtuous aspects of high income demand elasticities affecting rates of returns in investing in certain sectors (Dixon and Thirlwall 1975; McCombie and Thirlwall 1995; Schmookler 1962). Demand-pull factors have since then been considered key in guiding investment in innovation and explaining heterogeneity in return rates. Some empirical studies found a strong demand pull effect from exports markets in explaining innovation investments, especially in developing countries (Cirera, Marin, and Markwald 2015). This is likely the result of an increased demand from more tough and sophisticated markets. Aghion et al. (2018) also find evidence on the positive effects of demand shocks over patenting, with larger returns for more productive firms due to the competition effect discussed above.

There is a large literature analysing the negative impact of *uncertainty* on investment due to the existence of irreversibility.[7] A firm is more flexible to decide between inputs, technologies, and organizational set-ups before it takes the decision to invest in a particular machinery or to

[7] The papers by Caballero and Pindyck (1996) and Pindyck and Solimano (1993) show that the threshold of the marginal return on capital that triggers investment increases with the volatility of the marginal return, and therefore investment decreases with volatility. Caballero and Pindyck analyze US manufacturing industries, while Pindyck and Solimano's contribution is a cross-country study (indeed they found that the impact is larger for developing countries).

initiate a specific R&D project. Then, if uncertainty prevails over the future manifestation of relevant variables (e.g. interest rates, asset prices, exchange rates, input prices, labour costs, etc.) the firm might decide to postpone or cancel its investment decisions, either because it cannot foresee future returns on those investment projects in such an uncertain context, or because the expected rate of return that compensates for the increased risk is unachievable. Some papers also show that depending on production specialisation, the exposure to external shocks may also differ (Allayannis and Ihrig 2001; Campa and Goldberg 1995), and that diversification works as a mitigating factor for uncertainty (Koren and Tenreyro 2007). Industry and regional characteristics that shape the patterns of specialization, then, interplay in the role that macroeconomic uncertainty may have on R&D investment and its rewards.

Finally, the institutional framework "play the decisive role in shaping the kinds of skills and knowledge that pay off" (North 1990, p. 78). *Policies and regulations*, such as labour, tax, trade, foreign direct investment or competition policy, affect knowledge investment decisions and their returns (Cimoli et al. 2009; Hudson and Minea 2013). For example, rigidities in the contractual relations with skilled workers, the ability to import machinery or to hire foreign managers affect the effectiveness of R&D. Low and middle income countries' policy regimes change frequently and often imply higher costs of doing business (World Bank 2020), which act not only as a deterrent to entry of new innovative firms, but also to R&D investments of incumbents (for Latin America, see Katz 2001, where the response of innovative behaviour to the structural reforms of the 90s is studied). Institutions evolve within a logic that is system-specific, which implies that inefficient institutions might remain lengthily in specific contexts.

The discussion above is represented in Figure 1. Key elements defining market and knowledge context are listed on the left. Arrow flowing from contextual factors and pointing directly to firms' productivity (solid line) signals how the knowledge and market context shape firms' performance directly, while the arrow flowing to firms' returns to innovation investments (dotted line) represent how the context exerts influence also modifying the profitability of innovation efforts. The existence and importance of the latter channel is what we aim to empirically estimate.

3. Innovation investments, productivity and contextual diversity in Argentina

Latin American countries' total factor productivity has been falling in contrast to developed countries and also compared to developing ones that have shown a more successful performance, especially the East Asian Tigers (Crespi, Fernández-Arias, and Stein 2014). Within the context of low labour productivity of the region, Argentina performs better than Brazil and Mexico and similarly to Chile and Uruguay in 2019 (Figure 2). However, these last two countries have been increasing their productivity systematically since 1999 at an annual cumulative rate of 2.1% and 2.5% respectively, while Argentinean has only increased its labour productivity at 0.9% per year, a rate lower than Brazil's.

Firms' R&D expenditures in Argentina lags well behind developed countries and regional peers and does not show to be catching up. Argentinian firms invest just 2.2% of sales in innovation activities, compared to an average of 2.5% for Latin American countries (Crespi, Fernández-Arias, and Stein 2014).

Argentina has increased the amount of resources committed to R&D over the past years. Between 2007 and 2018, total expenditures in R&D rose resulting in an increase in the level of the R&D to Gross Domestic Product (GDP) ratio from 0.46% to 0.49% (Figure 3), positioning the country above its regional pairs with the exception of Brazil. However, this has been mainly a government investment effort. The share of R&D funded by firms during the same period is, on average, 22% of total R&D in Argentina; while firms' share of R&D is 45% in Brazil, 33% in Chile and 26% in Mexico.[8] One possible explanation for these low levels of firm's share in R&D are the expected low returns to R&D. Low R&D efforts made by firms may, in turn, explain why productivity has been stagnant in the country.

[INSERT FIGURE 2]

[INSERT FIGURE 3]

In fact, the ratio between labour productivity and firms' R&D expenditures, which can be considered as a first rough approximation to R&D returns, has fallen by 43% in Argentina (while only by 24% in Brazil between 2007 and 2017), suggesting that there is plenty of room for improving the profitability of firms' expenditures in R&D.

To fully benefit from R&D expenditure and encourage private participation, it is essential to identify the inefficiencies in the role of knowledge in the production function, which might be deterring the R&D contribution to labour productivity. When comparing sectoral R&D intensity and increases in labour productivity, the relationship is not always positive as it would be expected. Figure 4 shows that there are industries with high R&D intensity but low productivity growth and vice versa. This may be indicative of important inefficiencies in the role of knowledge in the production function, reducing private investments in R&D and constraining its impact on productivity. Market and knowledge contextual factors possibly have a role in pushing upwards or holding back the returns to private investment in innovation.

Indeed, sectors and regions in Argentina offer different market and knowledge conditions for doing business. These contextual characteristics are heterogeneous. For example, some regions

[8] Data source is the same as in Figure 3. Firms include public and private enterprises. In Brazil data is only available until 2017.

are better than others in attracting qualified labour. As can be seen in Figure 5a, the proportion of migrants holding a university degree is higher in Patagonia, while the northern region receives very little qualified workforce. Similarly, some sectors are subject to more volatile financial conditions[9] as shown in Figure 5b. Firms in different locations and economic sectors face different enabling or constraining conditions to innovation. Some of those conditions may affect firms' learning capabilities, their capacity to appropriate from the returns of their innovative efforts or other elements of the process of innovation. In what follows, we investigate the role of these contextual factors in explaining heterogeneity in the returns to R&D.

[INSERT FIGURE 4]

[INSERT FIGURE 5]

4. Methodology

As described above, our main goal in this paper is to understand knowledge and market contextual factors that affect the returns to innovative investments in Argentina. To this end, we use firm level data to estimate a knowledge-enlarged production function that includes interactions with variables representing key contextual characteristics described previously. These contextual variables will be measured at regional level, sector of activity level or at the sector/region level, depending on data availability. Next, we discuss data sources, variables definitions and the empirical strategy in detail.

[9] A detailed explanation on how this variable is measured can be found in Table A.1 of Appendix A.

4.1. Data sources

The main database for our analysis is the second "Employment and Innovation Dynamics National Survey" (hereafter **ENDEI 2**, for its acronym in Spanish). This survey covers the 2014-2016 period and was carried out jointly by the Labour and Employment Secretariat and the Science, Technology and Productive Innovation Secretariat. The sample was drawn so as to be representative of manufacturing firms with at least 10 employees, in terms of size (small, medium and large), region (five geographical areas) and sector (mostly 2 digits ISIC).[10] The sample includes 3.944 firms. We will use the previous ENDEI (hereafter **ENDEI 1**), which covered the period 2010-2012 and which is representative at size and sectoral level, comprising 3.691 firms, to construct some variables. Unfortunately, the survey was not designed to follow firms through time so it is not possible to match firms across waves.[11]

[10] Small firms are those with 10 to 25 employees; medium firms, those with 26 to 99 employees and large, those with 100 or more employees. Sectors included can be seen in Table 3. For some sectors of special interest, information was disaggregated at 4 digits. The five regions were: Patagonia (including provinces of Chubut, Neuquén, Rio Negro, Santa Cruz and Tierra del Fuego); Cuyo (including provinces of Mendoza, San Juan and San Luis); the Northern region (including Chaco, Corrientes, Formosa, Misiones, Catamarca Jujuy, La Rioja, Salta, Santiago del Estero and Tucuman); Pampeana (including Buenos Aires, Cordoba, Entre Rios, Santa Fe and La Pampa) and the region of the Capital city and suburbs. Information was disaggregated at province level.

[11] Sampling methods changed between both waves. In this respect, only ENDEI 2 is relevant for our exercise of assessing the role of regional/sectoral contextual factors since ENDEI 1 was not representative at regional level. Since waves cannot be matched at the firm level, we only use ENDEI 1 to build pseudo-panels at the size-sector-regional levels to construct some specific variables. This is the case of the firms' capital stock (see footnote 12) and the instrumental variable we use for some exercises (see Appendix B and in particular footnote 35 within this).

The variables used to measure the contextual factors are described in more detail below and are built using various data sources (See Table A.1 in Appendix A).

4.2. Empirical strategy

In order to estimate the average returns to innovation across all firms in our sample, we first estimate the knowledge production function specified in equation [1]. This baseline equation is a production function in per worker units, à la Griliches (1979), extended by knowledge. The dependent variable is value added per worker (VA_{it}/L_{it})[12] of firm i at year t, and inputs are: labour (L_{it}), capital stock per worker (C_{it}/L_{it}) and knowledge stock per worker (I_{it}/L_{it}).

We measure all variables in natural logarithms, assuming a log linear relationship between inputs and value added. Firm and time fixed effects are included in order to control for firm and time invariant unobserved heterogeneity.

As we aim to measure the effect of contextual factors on innovation returns, the baseline model expressed in equation [1] is expanded to include interactions between knowledge (K_{rst}) and market (M_{rst}) contextual factors (defined at sectoral (s) or regional (r) level or both), and investment in innovation. This allows to recover the influence of the different contextual factors over the innovation returns coefficient (equation [2]).

$$\frac{VA_{it}}{L_{it}} = \alpha + \beta L_{it} + \gamma \frac{C_{it}}{L_{it}} + \delta \frac{I_{it}}{L_{it}} + u_i + \tau_t + v_{it} \qquad [1]$$

[12] Results are robust when we use sales as a dependent variable and include expenditure in intermediate goods in the regression.

$$\frac{VA_{irst}}{L_{irst}} = \alpha + \beta L_{irst} + \gamma \frac{C_{irst}}{L_{irst}} + \delta_0 \frac{I_{irst}}{L_{irst}} + \delta_1 M_{rst} + \delta_2 K_{rst} + \delta_3 M_{rst} \frac{I_{irst}}{L_{irst}} + \delta_4 K_{rst} \frac{I_{irst}}{L_{irst}} + u_i + \tau_t + e_{irst}$$

[2]

Therefore, δ_0, δ_3 and δ_4 are our main coefficients of interest, as they estimate the effect of market and knowledge contextual factors on innovation returns. Besides, δ_1 and δ_2 will capture the direct influence of contextual factors over firms' productivity. Standard panel data procedures are used to produce estimates for coefficients.

4.2.1. Main micro variables definitions

Labour is measured as total employees. Capital stock is constructed using an estimation on energy, gas and fuel consumption from existing capital and new machinery acquisitions.[13] Regarding the main variable of interest, innovation investments, there has been an intense academic debate since the seminal work of Griliches (1967) on how to measure the knowledge

[13] We did not have information on capital stock. Thus, we proxied it using information on firms' expenditure on energy, gas and fuel and investment in machinery. The former proxies the initial stock of capital since it accounts for energy costs on *existing machinery* (Frank 1959) while the latter accounts for gross fixed capital formation during the period and is also measured in units of energy expenses, which makes the addition possible. We used the following equation:

$$C_{it} = \frac{Total\ Energy\ Costs_{sector-size}}{Total\ Wage\ Costs_{sector-size}} * Wage\ Costs_{it} + \frac{\Delta Energy\ Costs_{2010-12\ Sector}}{Investment\ in\ machinery_{2010-11\ Sector}} * Investment\ in\ machinery\ for\ Innov_{it} \quad [3]$$

The first term of the sum aims at measuring initial capital stocks at the beginning of each year, while the second is an estimate of each firm's capital formation during that year. The first factor in each term of equation [3] was calculated using information from ENDEI 1 due to lack of such data in the second wave of the survey.

stock using investment in innovation.[14] The literature has normally used in-house investment in R&D as a proxy, mostly because the lack of data on knowledge stock and the difficulties to estimate, for instance, organizational knowledge, which is complementary to any other source of knowledge. R&D is at best a key input among others when measuring knowledge capital formation. A challenge in building the knowledge stock variable is the lack of time series information on firms' innovation efforts, which implies that we cannot include lags in our estimation of the knowledge stock and needs to rely on contemporaneous investment as a proxy for the knowledge capital stock. However, when firms decide to invest in innovation, they anticipate that such efforts need to be sustained in the near future. Investment in R&D is, therefore, fairly sticky (Dosi 1988), and not expected to be subject to severe changes at micro level. As a result, the investment of a firm today relative to other firms in the present time can be considered a relevant proxy for the same indicator in the past. [15]

This behaviour is confirmed in our data (see Table 1): during the period 2014-2016 the percentage of firms investing in R&D is fairly stable, around 23% and 25% of the sample. Moreover, if we only consider firms with continuous investment of expenditures in R&D during the period - firms investing during 2014, 2015 and 2016 - the proportion is 22% of the sample (above 82% of firms investing in R&D, did so continuously during all years included in the survey), confirming the stickiness in R&D expenditures.

One final important methodological element relates to the measure of all relevant types of knowledge besides R&D. In this paper we also consider investment in design and industrial

[14] Griliches (1967) estimated that firm's R&D and firm's productivity were connected in a bell-shaped lag structure and since then several strategies have been followed normally using R&D and its lags.

[15] Bond and Guceri (2017) estimate the impact of R&D on productivity on a sample of UK establishments using both the estimated stock and the flow of investments with similar results.

engineering as part of these knowledge investment efforts (RD&D). The reason for this is twofold. Firstly, there are several manufacturing activities (e.g. wearing apparels) for which knowledge is mainly incorporated in the design production process. Since some contextual factors are measured at sectoral level, we need to be sure we incorporate the sectoral specificities in knowledge stock formation. Moreover, industrial engineering is particularly relevant for reverse engineering and technology adaptation which is the typical first stage in innovation learning (Katz 1982). Secondly, design and engineering implies in-house efforts that often cannot be distinguished from R&D efforts (Cox 1990), especially in the development stage. In many firms, these types of knowledge activities are largely performed by the same staff and are very difficult to disentangle one from another. In fact, all guidelines for innovation surveys, explicitly discuss that differentiating both types of knowledge is a difficult task.[16] Thus, our measure of knowledge stock formation adds design and engineering to R&D (labelled hereafter as RD&D). We replaced missing values of investment in RD&D by zero in order to avoid losing observations and we control for the potential underestimation of the stock of knowledge capital by including a dummy that indicates whether the firm reported missing

[16] In ENDEI the questionnaire reads: "Industrial Design and Engineering Activities: they are those activities carried out within the firm: technical functions for production and distribution not included in R&D, drawings and graphics for establishing procedures, technical specifications and operational characteristics; installation of machinery; industrial engineer; and production start-up. These activities can be difficult to differentiate from R&D activities; for this it can be useful to check if it is a new knowledge or a technical solution. If the activity is framed in the resolution of a technical problem, it will be considered within the Engineering and Industrial Design activities. It should include the annual salary of the staff devoted to these activities according to the time dedicated"

values ("Missing dummy").[17]

Table 1, below, shows that expenditures in industrial design and engineering are deployed by a stable subset of firms during the period, with 21% of firms investing in this category every year during 2014-2016. The last row shows that when considering RD&D, around 35% of firms invested in each year and 31% did so every year. These figures also imply that around 10% of firms in the sample invest continuously in Design and Industrial Engineering but not in R&D, which further validates our decision to include RD&D in the analysis.

[INSERT TABLE 1]

Table 2 shows some summary statistics of firm-level variables used to estimate equation [1] organised by firm size. All variables increase with firm size: larger firms have higher labour productivity but also much intensive use of capital and knowledge stock.

[INSERT TABLE 2]

4.2.2. Contextual variables definitions

After the discussion in the conceptual framework, three key knowledge contextual factors (two related to spillovers -sectoral and spatial- and one related to the role of policies supporting the knowledge supply) and four key market contextual factors (market competition, demand levels, uncertainty and regulations) were identified (see Figure 1). These factors may exert their influence at spatial and/or industry levels. To operationalise them quantitatively we build indicators at regional, sectoral or region/sector levels depending on data availability, theoretical

[17] In addition, we also summed 1 to all reported observations in the RD&D variable to avoid missing information when applying natural logarithms to zero values.

proximity to the contextual factor under study and degree of explanatory power to explain firms' productivity.[18] We describe below the variables we use to proxy for each contextual factor. Table A1 in Appendix A synthesises and presents additional details on contextual factors, variables definitions and data sources.

Knowledge contextual factors:

- **Sectoral spillovers** are proxied by *investments in innovation per sector-region*. This indicator is built summing up investment in all innovation activities per sector and region per year in ENDEI 2014-2016. The more firms in the sector-region invest in innovation the larger the potential for each firm to learn from their environment.
- **Spatial spillovers** are measured by *regional migrations of individuals holding university degrees*. We consider for each year the proportion of inhabitants of a province that are originally from another country or province and hold a university degree. This variable intends to measure the movement of qualified workforce that can facilitate spatial spillovers.
- **Support of knowledge supply** is proxied by *academic publications per sector*. We built this indicator using information from academic publications per year indexed in Scopus in different fields of studies, with at least one author affiliated to Argentinean institutions. Based on Albuquerque et al. (2015) this number of publications is translated into sectoral data using matrices for Argentina that measure how relevant is each field of study for each sector. Given that most academic researchers are funded by the state and publications are the main output to disseminate scientific knowledge, this indicator intends to measure public support to the creation of knowledge supply that

[18] More details on this selection procedure could be found in Arza et al. (2020).

may be relevant for firms in each sector.

Market contextual factors:

- **Competition** is measured using the sector-region *Herfindahl index* based on firm sales disaggregated at the sector, region, year level using information from ENDEI 2. This index measures market concentration and intends to account for the (inverse of) rivalry of each firm's experiences in each sector and region.[19] We expect market competition to have a positive effect on firms' productivity in a nonlinear way.[20]
- **Demand** is represented by the *exported value* measured per year at the province and sector levels. This indicator captures the context of international demand and indirectly demand-pull factors driven by opportunities to export in the sector and in the region. Export levels can boost innovative behaviour both for firms that are already exporting and others that may identify such opportunity driven by demand.
- **Uncertainty** is measured by the *unpredicted volatility of sectoral financial credit.* Following the literature we measure unpredicted volatility as the standard deviation of the residuals of the first-order autoregressive processes (AR(1)) (Aizenman and Marion 1999; Aizenman and Marion 2004; Chow et al. 2018; Jehan and Hamid 2017; Bloom et al. 2018). These AR(1) processes are estimated over the period with available data (2000-2017), with quarterly frequency of sectoral financial credits amounts. The dispersion of residuals accounts for 'unpredictable variability' and intends to capture uncertainty over the relevant period about the behaviour of this key variable (financial

[19] We are aware of the limitations of using the Herfindahl index to measure market competition, but due to data limitation we could not build alternative measures such as Lerner or Boone indexes (Boone 2008)

[20] We included the quadratic term of the Herfindahl index in the regression but we later dropped to save degrees of freedom since it was not significant.

credit) for business operation. A higher variance indicates that the variable is less predictable and therefore there is more uncertainty. The standard deviation was calculated annually and was standardised to have a mean of 0 and a standard deviation of 1.

- **Regulation** is proxied by *proportion of firms either entering or exiting the market per province*, using information from the Observatory of Employment and Entrepreneurial Dynamics (OEDE) from the Ministry of Labour. This indicator capture the business dynamism of each province; a higher value suggests that there are less barriers to entry or exit the market which may contribute to foster entrepreneurship (Klapper, Laeven, and Rajan 2006) and productivity growth.

Table 3 presents the rank order of each sector according to the mean of variables proxying different contextual factors. A low number represents that firms in the sector are in a relatively good position for that contextual factor. The last three columns correspond to average ranks for each dimension of contextual factors (knowledge and market). We highlighted the five best ranks in each dimension. As can be seen, the food sector is the one with better contextual conditions overall, especially regarding knowledge factors but also market factors. It is followed by 'other', possibly driven by the automotive and oil industries.[21] This does not come as a surprise since these are industries where Argentina has comparative advantages (Bekerman and Dulcich 2013), that have received policy support (especially the automotive industry) (Baruj et al. 2017) and where there is long historical experience in production, driving important technological opportunities (especially in the food sector) (Marín and Petralia 2018).

[21] These sectors fall in the 'other' category because of the survey confidentiality requirements, given that there are a few large firms in each of these sectors which would otherwise be easily identified.

[INSERT TABLE 3]

4.2.3. Addressing potential endogeneity

The potential for omitted-variable bias and simultaneity issues raises a challenge for the identification of the knowledge production function's coefficients. We address this endogeneity problem[22] by exploiting the panel structure of our data with the inclusion of time and individual fixed effects, as it has been done in other papers which use the ENDEI survey databases (see for example Brambilla and Tortarolo (2018)). Fixed effects will capture omitted variables that are constant though time for each firm, or across firms for a given year.

As an additional estimation of the relationship between R&D and productivity, and to analyse the robustness of our results, we also explore an instrumental variable (IV) approach. We use this methodology to estimate the returns to R&D on productivity as this is one of our main coefficients of interest. Specifically, we instrument investment in R&D using the proportion of firms within each sector-region-size group that suffered from import restrictions on goods essential for innovation before a sudden exogenous change in trade policies that occurred in 2015. Thus, we expect that firms that responded that suffered from severe obstacles to innovation related to import restrictions (for example, they could not import machinery or

[22] As firms construct their knowledge stock by investing in innovation activities, these decisions are very likely endogenous to firms' productivity, and exogeneity of regressors cannot be assumed. Unobservable omitted variables such as firms' workers' know-how or managerial capabilities could affect both firms' decisions regarding innovation, capital and labor, and firms' productivity. Additionally, while larger knowledge stocks may increase firm productivity, more productive firms are more likely to be exposed and aware of innovation opportunities. Hence, these firms may be more prone to investing in innovation and increasing their knowledge stock than less productive firms, causing reverse causality issues.

inputs needed for innovation) in 2013[23] are the ones that increased the most their investments as soon as restriction were eliminated in 2016. Appendix B explains this IV strategy in detail, which is used just to obtain unbiased estimates of the returns; so we can then be confident that the positive returns of R&D in terms of labour productivity, which is our baseline specification, are robust. However, when estimating the effect of contextual factors, we use the non-IV strategy, given the infeasibility to instrument all interactions.[24] While this approach does not allow a perfect identification of the size effects, we believe that the estimates still account for the impact of these contextual factors to the returns to R&D. Time and firm fixed effects, nevertheless, are included in all estimations throughout the study, which controlling at least partially for sources of potential endogeneity.

5. Results

5.1. Knowledge production function estimates

Column (1) in Table 4 shows the results for the baseline estimation of equation [1]. The dependent variable is value added per worker (*VA per worker*) and production factors include *Labour*, physical *Capital per worker* and knowledge capital (RD&D) per worker.

In addition to the baseline model, columns (2) - (5) of Table 4 present alternative specifications to check for i) the effectiveness and significance of estimation methods in dealing with potential endogeneity issues, and ii) robustness of estimated coefficients, mainly for the knowledge

[23] The year of fieldwork for the first wave, which collected data for 2010-2012.

[24] Given that we have only one valid instrumental variable, we decided not to instrument the interactions with all contextual factors. We would need to instrument eight variables (investment in RD&D and seven interactions) and we think this would lead to unreliable results.

capital stock proxy, which is the main focus of the study. We analyse the coefficients' stability estimating pooled OLS (column 2) using our preferred set of explanatory variables expressed as per-worker ratios. We also estimate panel regressions using variables in levels instead of the per-worker units (column 3); and pooled OLS (column 4) and panel (column 5) regressions using R&D instead of RD&D as proxies of knowledge stock.

Our preferred specification corresponds to column (1) since it includes time and firm fixed effects. Labour, physical capital and RD&D are statistically significant and show the expected signs: a 10% increase in RD&D per worker increases productivity in 0.09%, and a 10% increase in the proxy for physical capital per worker increases productivity in 3%. The coefficient for labour is significant and negative, which implies decreasing returns to scale.[25]

Results are fairly robust for different specifications; RD&D coefficients are always positive and significant, and the coefficients' size is relatively stable in panel data estimations (columns 1, 3 and 4). For pooled estimations, in contrast, the coefficient is much larger (1.7 times larger than FE, column 2 against column 1), which suggests that the effect of omitted variables on RD&D and productivity goes in the same direction. This could be the case, for example, of managerial capabilities or entrepreneurial quality, which affect both RD&D and productivity positively (better ability to manage R&D projects and production processes in general).[26]

[25] In all estimations of Table 4, except for column (3), variables are expressed in per worker units. As our model is linear in logarithms, we can assume a Cobb-Douglas specification: $Y = AL^{\theta}C^{\gamma}I^{\delta}$ and dividing by L: $\frac{Y}{L} = \left(\frac{A}{L}\right)L^{\theta}L^{\gamma}L^{\delta}\left(\frac{C}{L}\right)^{\gamma}\left(\frac{I}{L}\right)^{\delta} = AL^{\beta}\left(\frac{C}{L}\right)^{\gamma}\left(\frac{I}{L}\right)^{\delta}$ with $\beta = \theta + \gamma + \delta - 1$. Hence, a negative coefficient for L implies that $\gamma + \delta + \theta < 1$ i.e. decreasing returns to scale.

[26] When knowledge stock is approximated by R&D we also find the significant and positive effect on productivity. However, when comparing results for R&D with and without FE (columns 4 and 5), the bias is

The coefficient for our proxy of physical capital stock is very robust. Labour seems to be more correlated with omitted variables, as the coefficient is positive for the pooled estimation, but otherwise negative and consistent across panel specifications.

As our coefficients are measured in elasticities, we convert them into returns to innovation in monetary units - i.e. how many monetary units value added per worker increases per monetary unit invested in RD&D. Figure 6 shows the firm level distribution of these returns.[27] The distribution of returns is highly skewed to the right: many firms have low returns to their investments in innovation, while a few have very high returns. More than half of the firms have returns lower than one. This means that for over 50% of the firms, investments in innovation are less than compensated by increases in value added contemporaneously.[28] Yet, the average value of returns for the sample is two units per monetary unit invested. Additionally, returns across firms show high dispersion, with a standard deviation four times greater than the mean. This justifies our goal of analysing the sources of heterogeneity of returns.

[INSERT TABLE 4]

[INSERT FIGURE 6]

negative, which means that if caused by omitted variables, they are correlated in opposite directions with R&D and with productivity. For example, there may be omitted innovative efforts which work as substitutes of R&D (but affect productivity positively), such as, possibly, design and engineering, since as we commented above it is very difficult for respondents to empirically discriminate them from R&D

[27] Firms with zero investment in RD&D are not included

[28] We estimated the short-run returns, but investment in RD&D may have higher returns in the longer term depending on the project nature.

5.2 Measuring returns to investments in knowledge by sector and region.

As the focus of our analysis is to explain heterogeneities in RD&D returns through the influence of contextual factors measured at the sectoral and regional levels, in this section we estimate equation [1] by sector and, in turn, by region using the preferred specification in column (1) from Table 4.

Coefficients for sectoral returns of RD&D are presented in Figure 7, showing significant heterogeneity and confirming that returns to RD&D are largely sector specific.[29] The returns, proxied by estimates of RD&D elasticity on labour productivity, appear to be particularly large for Wearing Apparel (ISIC 18), Machinery for Agriculture (ISIC 2921) and Pharmaceutical (ISIC 2423), although the latter coefficient is not significant.

When we measure the returns to RD&D by sector in monetary values[30] instead of elasticities (see estimates in Table C.1 of the Appendix C), Wearing Apparel remains the sector with highest returns, followed by Electric Material, Radio and TV (ISIC 3012), and the Pharmaceutical industry. The order of the sectors according to RD&D returns in monetary terms does not significantly change compared to that of elasticities. Additionally, for 18 of the 27 sectors, mean monetary returns to RD&D are above one. Hence, for more than half of the economic sectors, on average, firms increase their productivity in more than one unit for every monetary unit invested in RD&D.

[INSERT FIGURE 7]

[29] F-test statistic for the null of equality of coefficients across sectors is rejected at 1% level of significance.

[30] Sectoral and regional returns in monetary values were calculated as the mean value of individual firm returns within each sector and, in turn, region.

Figure 8 presents the returns to RD&D when calculated separately by regions. The figure shows that except for the returns in the Patagonia region,[31] there is less heterogeneity across regions,[32] which is likely the result of the data at regional level being too aggregated. The ordering of returns across regions is maintained if we consider monetary values instead of elasticities.

[INSERT FIGURE 8]

RD&D returns at the sector-region disaggregation (not presented here), also show high heterogeneity, with the F-test for the null hypothesis of coefficients equality rejected at the 1% level. In sum, data sustain that returns to RD&D differ significantly. In what follows, we analyse the drivers of this heterogeneity assessing the role of contextual knowledge and market factors in boosting or lowering the returns to innovative activities.

5.3. The role of contextual factors

Table 5 present estimations for equation [2]. Results suggest several interesting findings. Both **sectoral spillovers** (expenditure on innovation per sector/region) and **demand** factors (sector/region exports) are positively correlated with productivity levels. The Herfindahl index shows a negative and significant coefficient, indicating that as markets become more concentrated, firms become less productive on average. In other words, **Competition** exerts a positive effect on firm's productivity.

[31] Patagonia region is a special case in terms of labour productivity since it is specialized on capital and natural-resources intensive industries and receives strong fiscal and economic support from the state for certain economic activities.

[32] F-test for the null of equality of coefficients is not rejected at the usual significance levels in this case.

Returning to Figure 1, these findings confirm the influence of some contextual factors on firm productivity through channels other than RD&D returns. This has been depicted in solid line in the Figure and occurs for some knowledge contextual factors (sectoral spillovers) and market contextual factors (demand and competition). Examples of alternative channels could be that firms design other strategies apart from RD&D investments to absorb innovation spillovers; or alternatively that higher levels of competition can lead managers to invest more in workers' training, which are not measured in our estimations.

We also find empirical support in the role of contextual factors shaping RD&D returns. **Spatial spillovers** (proportion of university immigrants per province) and **uncertainty** (volatility of sectoral financial credits) have a significant relationship with productivity *through RD&D returns*. For the former, a positive coefficient for the interaction indicates that investments in RD&D have a higher return on productivity among firms located in areas with a higher inflow of migrants with university degrees. This situation is characteristic of the Patagonian region, which has the highest level of immigration of skilled workers (see Figure 5a), especially motivated by public policies attracting qualified workforce to this area; and the highest returns to innovation (as seen in Figure 8). This result is not surprising and could be led by the fact that a higher supply of educated workforce increases RD&D returns, or that more productive and innovative areas attract people with higher educational levels. Results for uncertainty are also as expected; sectors that suffered from more financial volatility, show lower returns to innovation. This is the case, for example, of the metal and meat industries which show high levels of financial volatility (Figure 5b).

The results also show a negative and significant coefficient for the interaction between **support to knowledge supply** (proxied by academic publications per sector) and RD&D. This is a puzzling result. We argue that firms in contexts which are richer in knowledge creation can rely more on external research to innovate, either by reading scientific publications or by contracting consulting services carried out by scientists working in the national scientific sector, rather than investing in RD&D themselves. Hence, in these contexts, the benefits of internally investing in RD&D are lower. We find some indirect evidence for this hypothesis in the fact that 37% of firms invest in RD&D in contexts with low publications levels, compared to 31% in contexts with high publications levels.[33] This seems to indicate that in sectors with greater availability of relevant academic publications, such as Chemical Products and Food, for example, firms rely less on their own innovation investments, and more on the knowledge absorbed from their context. Another possible explanation is the competition between the academic and productive organisations for skilled labour in sectors with a greater academic development. In these sectors, more skilled people may go into the academic sector, decreasing the availability of high educated workforce for private firms with a consequent effect on RD&D returns.[34]

All in all, the contribution of all knowledge factors on total returns to RD&D is 28%, which provides support for policies aiming at boosting knowledge capacity building processes in the production context.[35]

Going back to Figure 1 we found some empirical support for the relationship depicted though the dotted arrow, flowing both from knowledge contextual factors (support of knowledge

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[33] Low publication levels are sectors in the first quartile of the distribution of publications, while high publication levels are those in the fourth quartile.

[34] We thank an anonymous reviewer for bringing this possible alternative explanation.

[35] Calculated from Table 5 using the mean values of explanatory variables. We thank an anonymous referee for suggesting this calculation.

supply and spatial spillovers) and market contextual factors (uncertainty), explaining heterogeneous returns to RD&D.

Finally, **regulatory** measures have no significant incidence on firm's productivity, neither directly nor through and effect on the returns to R&D. This can be the result of a lack of appropriate measurement, as a vast literature suggests that regulatory environment affect innovation incentives and firms' performance.

[INSERT TABLE 5]

A visual representation of the results discussed above can be seen in figures 9a to 9c. To construct each plot, we divided the sample of firms into two groups by the median value of some of the contextual variables with a significant interaction term in the regression. The figures show the density plots of RD&D returns using results from estimation of equation [2] for each subgroup of firms, based on being above or below the median value for support of knowledge supply (panel (a)), uncertainty (panel (b)) and spatial spillovers (panel (c)). It can be seen that in contexts with higher levels of publications, less educated migrants and more uncertainty, firm RD&D returns are notoriously displaced to the left. In all cases, the mean value of RD&D returns for firms in the left sided distribution is below one, while it is above one for the other group. This indicates that on average, only for firms in the right side of the distribution value added increases more than one unit per monetary unit invested in RD&D.[36]

[INSERT FIGURE 9]

[36] In the three cases depicted, the Kolgomorov-Smirnov test rejects the null hypothesis of equality of distributions, indicating that the distributions of returns are statistically different between groups.

6. Conclusions and implications for policy

This paper builds a conceptual framework integrating various arguments on the role of contextual factors on long-term investment. From innovation systems literature we emphasise the role played by the knowledge context. In turn, we integrate arguments from neoclassical, institutional and demand-driven theories to claim that there is an equally important contextual dimension related to market conditions affecting investment returns.

Using this framework we bring new evidence on what factors affect the returns to innovation in Argentina, which helps to explain the dismal low volume of private R&D investments. Firms' innovation investments and their returns depend both on the internal processes and characteristics of the firms, and the environment within which firms actively operate and interact. This external context can be characterized by a set of knowledge factors that affect firms' learning opportunities, and a set of market factors, that shape incentives to allocate resources and the realization of profits coming from these investments. Our results show that these contextual factors significantly affect firms' productivity through shaping the profitability of innovative investments, which explains the observed heterogeneity in returns.

The results from estimating a knowledge production function enlarged to account for these contextual factors, show that the returns are indeed quite heterogeneous; with most firms having low returns and not compensating their innovative expenditures with productivity gains; at least in the short term. This translates into the fairly disappointing level of in-house private investments in R&D and low productivity growth. The findings also suggest that certain contextual factors, both related to knowledge and market dimensions and that we measure at the regional and sectoral level, affect these returns.

Specifically, we find that **uncertainty** affects innovation returns negatively as more volatile markets do not favour returns to investments. On the other hand, **spatial spillovers** hold a positive relationship, enhancing returns to RD&D through the firms' knowledge environment. In turn, **competition**, **demand** and **sectoral spillovers** have a positive significant relationship on productivity directly, although we do not find evidence of an impact via the RD&D returns. In addition, an unexpected result is the negative effect of **support of knowledge supply**, proxied by industry relevant academic publications, on RD&D returns. We conjecture that as firms in sectors with a greater scientific endowment absorb more knowledge from their context, the benefits from internally investing in innovation are lower.

There are some caveats for our analyses that should be stressed. One limitation of the analysis is that our micro data covers a short period of time (three years). Thus, it may be the case that some contextual factors, for example regulation, need longer periods for their effects to become noticeable. Another potential caveat when interpreting the results is that a robust assessment of the causal relationship between contextual factors, RD&D and productivity is challenging with limited instruments available. However, the results are fairly stable to different specifications, and panel data estimation helps minimizing some of the potential endogeneity issues. Going forward, however, it is important to invest on generating better data, including longitudinal data, to improve the identification and causal interpretations of the coefficients.

Implication for policy

Argentina's STI policy has been traditionally characterized by a greater focus on science and research (Albornoz 2004). This has changed in the turn of the 21th century and there are now new funding schemes specifically supporting private innovation. In 2019 the amount allocated by the Argentinean Agency for the Promotion of Science and Technology (ANPCYT) to innovation projects in the private sector (FONTAR programme) is of similar magnitude to that allocated to scientific projects (FONCyT programme). However, the trend's slope is considerably steeper for the former. Out of the total budget, the proportion of funds allocated to FONTAR grew in 18 percentage points in the period 2009-2019, while such growth was 10 percentage points for FONCYT funds (those oriented towards specific sectors reduced their participation). However, in the international comparison the country still shows a low proportion of policy tools oriented towards the promotion of linkages between the scientific and the private sector in contrast to other countries such as Mexico and Brazil (Macchioli and Osorio 2017). It is true that there are specific programmes oriented towards improving innovation in some sectors (e.g. FONARSEC programme) and regions (COFECYT programme), but the amount of their budgets is marginal when compared with the previously mentioned programmes[37]. Innovation policy tools in Argentina are rather horizontal (Arza et al. 2018) and their institutional design is defined at national level (Niembro 2019) with the budget allocation highly concentrated in central regions (Niembro and Starobinsky 2021). Firms investment in innovation is still importantly affected by cost, market and knowledge obstacles (Arza and López 2021) which may explain why private R&D remains below regional peers such as Brazil and Chile. This paper shows that the low aggregate R&D can be explained by low returns with large regional and sectoral heterogeneity, which imply that in order to encourage more private R&D activity there is a need to address these contextual constraints. We also found that knowledge contextual factors have a positive impact on the returns to

[37] Each of them represented around 13% of FONTAR budget in 2017. Data from FONARSEC and FONTAR available at ANPIDTYI-MINCYT (2020); data from COFECYT comes from the government webpage [https://www.argentina.gob.ar/ciencia/cofecyt/convocatorias/pfip-2017, accessed on November 2021].

investment in innovation, which provides further evidence on the need to boost knowledge spillovers in specific contexts.

First, uncertainty plays a negative significant impact to the returns to R&D and policies looking to incentivize innovation should focus on supporting firms' R&D investment in periods of economic uncertainty. While macro stability is a necessary condition to increase private R&D investments, predictability of existing policies to encourage R&D is also important, but innovation strategies and priorities have shifted across governments in the last decades (Arza et al. 2018). A more medium-term strategy is necessary to reduce such uncertainty.

Second, promoting instruments that facilitate spatial spillovers, such as PhD internships or research industry collaboration programs can also play an important role in incentivizing R&D investments in specific regions. This contrasts with the current narrow focus in incentivizing innovation mostly through subsidies and credits and productive development via the use of tax incentives (Gurcanlar et al. 2021) .

Third, although our evidence shows that sectoral spillovers are not statistically significant in boosting R&D returns, they increase firm level productivity through other channels. Hence, public policies should focus on providing an adequate environment for firms to benefit from external knowledge, as this has a positive effect on their productivity.

Forth and more importantly, the impact of these contextual factors on R&D largely supports the need for more flexible and decentralized innovation policy. STI in Argentina remains largely centralized (Niembro 2019) and contextual heterogeneity points out to the need of regional and sectoral STI strategies. Policies developed from the centre, with little adaptation to local specificities, will likely fail in addressing critical deficiencies in a specific context.

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Declaration of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A: Contextual factors operationalisation

Table A.1: Contextual factors, variables' definitions and sources of information

Contextual dimension	Contextual factors	Variable (vary by sector/region)	Units of measurement	Explanation	Data source
KNOWLEDGE CONTEXT	Sectoral spillovers	Investment in innovation (sector and region)	In tens of billions of pesos	Results from adding up investment in any innovation activity for firms within same sector and region	ENDEI 2 2012-2014
	Spatial spillovers	Proportion of immigrants with university degree (region)	Proportion (0-1)	Proportion of inhabitants of a province that are immigrants, i.e. originally from another country or province, and hold a university degree	Permanent Household Survey (EPH)
	Support to knowledge supply	Academic publications (sector)	In tens of thousands	Built from Scopus microdata on academic publications by at least one author with affiliation in Argentina. Each publication is assigned a field of study by Scopus. To convert this to sectoral level data, we use a matrix built from ENIT 1998-2001 data which offers information on how much each sector of economic activity values each field of study, as suggested by Albuquerque et al (2015).	Scopus + ENIT (National Survey on Innovation and Technological Behaviour)
MARKET CONTEXT	Competition	Herfindahl index (sector and region)	Index (0-1)	Sector-region Herfindahl index constructed with firm level sales data from ENDEI using expansion factors	ENDEI 2 2012-2014
	Demand	Exports (sector and region)	In hundreds of millions of US Dollars	Value of yearly exports in dollars by province and sector. Prices adjusted with sectoral level price indices	COMTRADE; Fares, Zack, and Martínez (2017); for price adjustments
	Uncertainty	Volatility of financial credits (sector)	Standardised index (0 mean, variance 1)	Standardised index of standard deviation of residuals of AR(1) model using quarterly data on financial credits at sectoral level, calculated per year	Central Bank of Argentina (BCRA)
	Regulation	Proportion of opening and closing firms (region)	Proportion (0-1)	Calculated as the sum of firms entering and exiting each province market divided the total number of firms in each province	Observatory of Employment and Entrepreneurial Dynamics (OEDE) from the Ministry of Labour.

Appendix B: Instrumental variables estimation

Our IV procedure serves as an additional estimation of the returns of innovation investments on productivity. The results are in line with our main estimation of equation [1] presented in Table 4, giving additional evidence on this positive and significant relationship.

Our IV candidate exploits a pseudo-panel built by merging the two waves of the ENDEI survey. Although we cannot match firms across waves, we proceeded to match them at the sector-region-size level.[38] Hence, we propose to instrument RD&D intensity change in the ENDEI 2 period using the sector-region-size proportion of firms claiming to suffer from import barriers for innovation coming from the ENDEI 1 wave.

An essential aspect to understand the rationale for this IV candidate is the fact that in December 2015 there was a change in government in Argentina. Therefore, during the ENDEI 1 period (2010-2012) and the first two years of ENDEI 2 period (2014-2015), the leading political party was different from the one present during the last year covered by the ENDEI 2 survey, which ensures exogeneity of the policy change. This change in administration implied that regulations and restrictions on trade policies, which were highly present during the ENDEI 1 reference period and especially at the time when the survey was conducted (2013), were starkly alleviated

[38] This is possible given that samples were constructed to be representative of the Argentinean manufacturing sectors (by industry-size). However, as ENDEI 1 was not constructed to be representative at the regional level, we could not divide the sample into the same regions as ENDEI 2. We therefore made an ad-hoc split of the sample considering that cases were relatively balanced: "Region" is taken as a dichotomous variable signaling if the firm belongs to the Gran Buenos Aires region -comprising Ciudad de Buenos Aires and the main adjacent districts which belong to Buenos Aires Province- or to the rest of the country.

during the last year covered by the ENDEI 2 survey (2016) and even more when it was conducted (2017-8).

This IV strategy rests on the idea that regulations and restrictions on trade policies imposed by the government affected the perceived obstacles to innovation in an heterogenous way for firms of different sizes, sectors and regions, which in turn may have restricted the resources dedicated to innovation activities. We claim that import barriers on key goods for innovation activities are sensitive to regulations and trade policies. We would then expect that changes in trade regulations in 2016 decreased perceived obstacles to imports of goods for innovation activities, and consequently foster investments in innovation between 2014 and 2016.

Hence, we proxy a firm's restrictions on imports in 2014 through the sector-region-size *proportion of firms* claiming to suffer from import barriers during the ENDEI 1[39] period and assume that firms belonging to the same group are similarly affected by these barriers. Hence, our instrument's variability comes from differences in the intensity of perceived obstacles to imports across sector-region-size groups of firms. We then observe how these perceived obstacles relate to the *change* in innovation investments between 2014 and 2016, as between these two years firms were released from a battery of imports regulations. We expect a positive correlation between obstacles perception in the past and the change in innovation investment, as firms that were more restricted are the ones that experienced a higher increase in investment in innovation activities once these restrictions were removed. The conditional exogeneity assumption is plausible, given that import restrictions on goods which *are key for innovation*

[39] We assume that restrictions present during ENDEI 1 period (2010-12) can represent restrictions in 2014, as the political administration was the same during both periods, as well as trade regulations.

are expected to impact productivity levels precisely through its effects over the firm decision to conduct or increase its innovation activities, once these barriers are alleviated.

It is important to highlight that the constructed IV have a cross-section nature, and they are used to instrument the *difference* in innovation investment intensity between 2014 and 2016. As a result, the database loses its panel data structure. First differences, however, eliminate the effect of time invariant omitted covariates.

As can be seen in the first stage results (Table B.1, col 2), the instrument is significant and holds a positive coefficient. As expected, firms which suffered more from obstacles had a greater increase in their RD&D investments between 2014 and 2016. Additionally, the test for weak instruments (Montiel Olea and Pflueger 2013), which considers the clustered error structure of the models, gives evidence of rejecting weak instruments hypotheses.[40]

Second-stage results (Table B.1, col 3) show that physical capital proxy and labour coefficients are fairly robust, being the capital coefficient close to 0.3 and labour coefficient insignificant, as in the OLS estimation using variables in differences (Table B.1, col 1). As in our main specification, RD&D coefficient shows a positive and significant impact in labour productivity. However, the magnitude of the coefficient is significantly larger than the specification without instrumenting (Table B.1, col 1).

This increase in the coefficient may be explained by the fact that instrumental variables procedure estimates the *local average treatment* (LATE) effect rather than the average treatment effect for the whole sample. The estimated causal relationship by using the proposed

[40] The test rejects the null hypothesis that the Nagar bias of the second stage coefficient of RD&D exceeds a 20% of the "worst case bias", i.e. the case in which instruments are completely uninformative and first and second stage errors are perfectly correlated.

IV should be interpreted as the returns of RD&D investments for a sub-group of firms (commonly called *compliers*) which actually accept the "treatment". Our instrument varies among groups of firms, and it is not expected that all firms in each group will be equally affected by the instrument. The *compliers* in our IV estimation refer to those firms which actually increased their imports of goods essential to innovation due to the elimination of import barriers. If this subgroup of firms happens to have higher returns to innovation on average than the whole sample, the LATE (measured in the IV estimation) will effectively be higher. In order to evaluate if this is a plausible explanation for the increase in the size of the coefficient, we estimate our main IV specification (with the variables in differences 2014-16) by OLS for a subgroup a firms that claim to suffer from obstacles to import goods key for innovation in the 2^{nd} wave of ENDEI. This is a proxy for identifying the *compliers* in our IV estimation. In this estimation, the coefficient for RD&D increases to 0.14 (more than twice the size of the coefficient for the whole sample, column (1)). This gives favourable evidence towards the hypothesis that the compliers in our IV estimation have higher returns on RD&D on average than the whole sample, causing a rise in the coefficient.

In sum, despite the increase in the magnitude of the coefficient. The IV estimation shows further evidence on the positive and significant relationship between RD&D and productivity.

Table B.1: Instrumental Variables estimation

Variables Dep. Variable	(1) OLS estimates VA per worker	(2) First Stage RD&D	(3) GMM estimates VA per worker
Prop. of firms affected by barriers to imports		**0.96***** **(0.27)**	
RD&D per worker	**0.0067*** **(0.0037)**		**0.146**** **(0.065)**
Capital per worker	0.32*** (0.041)	0.12 (0.11)	0.30*** (0.043)
Labour	-0.027 (0.048)	-0.21** (0.089)	0.006 (0.049)
Missing dummy	0.048** (0.024)	-0.24 (0.15)	0.077** (0.035)
Constant	0.33*** (0.027)	0.065 (0.1)	0.28*** (0.028)
Observations	2,949	2,949	2,949
R-squared	0.055	0.008	

Note: Standard errors are clustered at the sector-size level

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

Appendix C: Average returns to RD&D in monetary values by sector and region

Table C.1: Mean values by sector and regions of firm returns calculated from equation [1]

Sector	Returns to RD&D	Region	Returns to RD&D
Wearing apparel	17.56	Patagonia	15.19
Electric material, radio and TV	14.80	Cuyo	3.79
Pharmaceutical products	10.45	North	3.15
Other metallic products	8.16	CABA	2.13
Machinery for agriculture	8.09	Pampeana	1.22
Equipment for domestic use	7.12		
Paper	6.76		
Textile products	5.65		
Other non-metallic minerals	5.50		
Edition	5.41		
Wood	5.31		
Car Parts	4.34		
Tools and machinery in general	3.38		
Furniture	3.27		
Basic metals	2.91		
Rubber and plastic products	2.76		
Other transport equipment	2.66		
Wine and other beverages	2.17		
Medical instruments	0.12		
Machinery and equipment	-0.14		
Meat industry	-0.35		
Others	-0.78		
Chemical products	-2.46		
Food	-2.96		
Dairy products	-3.74		
Trailers and semi-trailers	-7.81		
Leather	-8.07		

Note: These values are the yearly monetary returns of one peso per worker invested in RD&D on the value added per worker. They were calculated as the mean value of individual firm returns within each sector or region.

Tables

Table 1: Number of firms investing in Research and Innovation (R&D) and in Industrial Design and Engineering, 2014-2016

Number of firms investing in:	**2014**	**2015**	**2016**	**In all years (2014, 2015 and 2016)**
R&D	911	953	974	856
% of total firms	*23%*	*24%*	*25%*	*22%*
Industrial design and engineering	908	958	964	834
% of total firms	*23%*	*24%*	*24%*	*21%*
RD&D (rows 1 or 2)	1323	1379	1397	1235
% of total firms	*34%*	*35%*	*35%*	*31%*

Source: ENDEI 2

Table 2: Summary statistics for variables in the production function (baseline regression), 2014-2016

		VA per worker (in 10 thousands of pesos)	**RD&D per worker (in thousands of pesos)**	**Capital per worker (estimated energy consumption per worker) (in thousands of pesos)**	**Labour (employees)**
Small (10-25 employees)	Mean	49.49	3.09	18.03	15.70
	Std dev	69.12	16.90	28.90	5.43
	Var coef	1.40	5.47	1.60	0.35
Medium (26-99 employees)	Mean	60.62	4.86	27.38	47.08
	Std dev	76.49	19.33	28.79	20.80
	Var coef	1.26	3.98	1.05	0.44
Large (>99 employees)	Mean	82.27	6.30	46.69	448.94
	Std dev	127.19	19.29	50.15	668.11
	Var coef	1.55	3.06	1.07	1.49
Total	Mean	60.74	4.44	27.35	120.07
	Std dev	88.33	16.40	32.39	353.80
	Var coef	1.45	3.69	1.18	2.95

Sources: ENDEI 2 and ENDEI 1 (for estimation of capital stock)

Table 3: Rank order of sectors according to contextual factors (average 2014-2016)

	Contextual factor:	Support knowledge supply	Sectoral spillovers	Spatial Spillovers	Competition	Demand pull	Uncertainty	Regulation	Knowledge contextual factors	Market contextual factors	All contextual factors
	Variable	Academic publications (sector)	Investment in innovation (sector and region)	Proportion of immigrants with university (region)	Herfindahl index (sector and region)	Exports (sector and region)	Volatility of financial credits (sector)	Proportion of opening + closing of firms (region)			
		Rank	Rank	Rank	Inverse Rank	Rank	Inverse Rank	Rank	Average Rank	Average Rank	Average Rank
15	Food	2	12	1	22	1	19	1	5	11	8
1511	Meat industry	2	18	13	8	8	26	8	11	13	12
1520	Dairy products	2	4	20	23	6	12	7	9	12	11
1552	Wine and other beverages	2	25	16	20	4	21	11	14	14	14
17	Textile products	9	23	5	3	16	8	6	12	8	10
18	Wearing apparel	19	21	24	2	23	11	12	21	12	16
19	Leather	15	24	14	17	12	6	16	18	13	15
20	Wood	14	27	8	11	18	1	3	16	8	12
21	Paper	25	20	19	19	19	5	18	21	15	18
22	Edition	20	26	10	9	24	3	9	19	11	14
24	Chemical products	6	3	23	18	3	24	13	11	15	13
2423	Pharmaceutical products	6	1	27	10	14	24	23	11	18	15
25	Rubber and plastic products	23	9	7	14	9	7	10	13	10	11
26	Other non-metallic minerals	18	15	6	15	21	9	4	13	12	13
27	Basic metals	21	5	25	24	7	27	20	17	20	18
28	Other metallic products	16	17	3	5	22	10	2	12	10	11
29	Machinery and equipment	10	10	17	25	11	13	22	12	18	15

299	Tools and machinery in general	10	13	21	4	10	13	25	15	13	14
2921	Machinery for agriculture	10	8	11	27	5	13	14	10	15	13
33	Medical instruments	8	14	18	1	25	2	27	13	14	14
35	Other transport equipment	22	16	15	21	27	23	17	18	22	20
36	Furniture	17	19	22	13	17	4	15	19	12	15
2930	Equipment for domestic use	10	7	9	16	15	13	26	9	18	14
3012	Electric material, radio and TV	24	11	2	7	20	20	24	12	18	15
3420	Trailers and semi-trailers	26	22	26	12	26	17	19	25	19	21
3430	Car parts	26	6	12	6	13	17	21	15	14	14
9999	Others includes tobacco 16, cars 341, oil 23 and recycling 37	1	2	4	26	2	22	5	2	14	9

Source: Own elaboration based on different sources, see Table A.1 in Appendix A. Ranks are calculated using mean values for each variable calculated from our sample of firms. Highlighted cells mark the best five sectors in knowledge, market and all contextual factors.

Table 4. Results for baseline estimation of equation [1]

	(1)	(2)	(3)	(4)	(5)
Variables	**VA per worker**	**VA per worker**	**VA**	**VA per worker**	**VA per worker**
Capital per worker	0.30***	0.32***	0.33***	0.32***	0.30***
	(0.032)	(0.032)	(0.038)	(0.032)	(0.032)
RD&D per worker	**0.0088****	**0.015*****	**0.0083****		
	(0.0035)	(0.003)	(0.0035)		
Labour	-0.26***	0.062**	0.30***	0.068**	-0.20***
	(0.045)	(0.028)	(0.11)	(0.028)	(0.048)
R&D per worker				**0.017*****	**0.074*****
				(0.003)	(0.019)
Dummy 2015	0.18***	0.17***	0.18***	0.18***	0.18***
	(0.015)	(0.014)	(0.016)	(0.013)	(0.015)
Dummy 2016	0.35***	0.35***	0.33***	0.34***	0.34***
	(0.023)	(0.021)	(0.026)	(0.021)	(0.023)
Missing dummy	0.090*	0.061*	0.08	0.068*	0.85***
	-0.048	-0.033	-0.048	-0.037	-0.23
Constant	10.6***	9.26***	10.7***	9.27***	10.4***
	(0.38)	(0.29)	(0.4)	(0.28)	(0.38)
Observations	9,246	9,246	9,254	9,246	9,246
R-squared	0.39	0.159	0.397	0.158	0.393
Number of ID	3,489	3,489	3,490	3,489	3,489
Firm FE	Yes	No	Yes	No	Yes

Note: Standard errors are clustered at the sector-size level

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

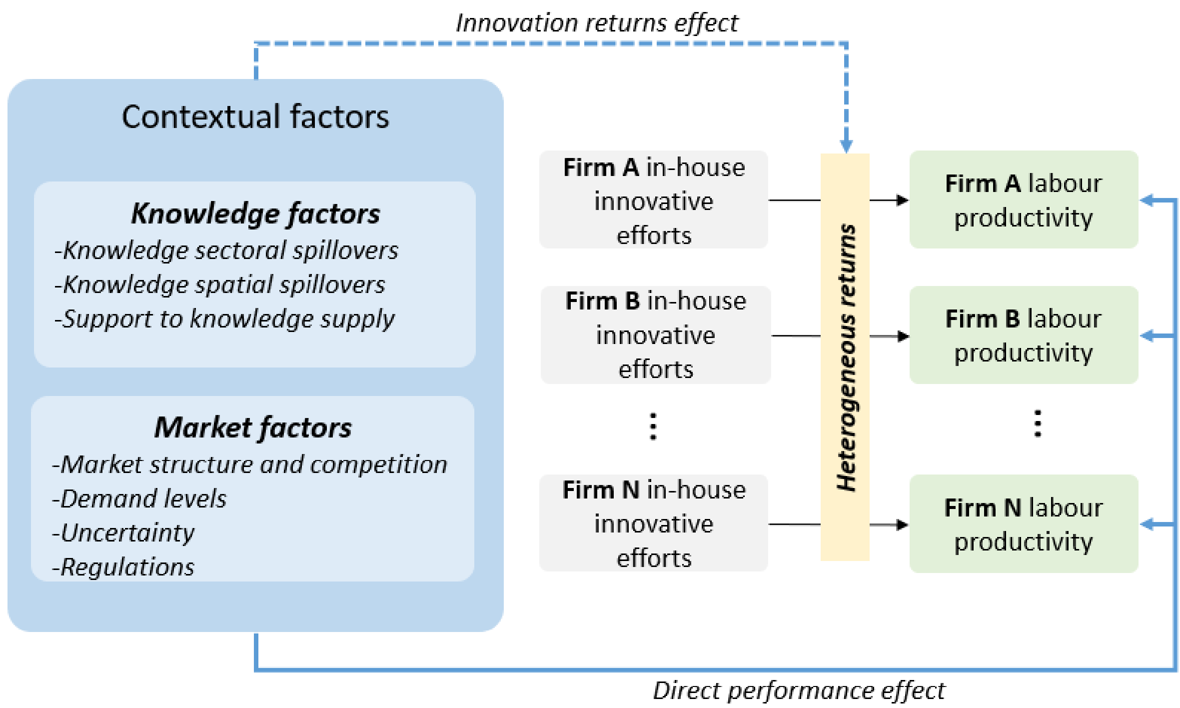
Table 5: Results for estimation of equation [2] on VA per worker

Contextual Factors		Variables	Coefficient
		Capital per worker	0.30*** (0.032)
		RD&D per worker	-0.003 (0.012)
		Labour	-0.26*** (0.046)
Knowledge contextual factors (direct effect)	*Support of knowledge supply*	Academic publications (sector)	8.81 (8.5)
	Sectoral spillovers	Investment in innovation (sector and region)	3.08*** (1.14)
	Spatial spillovers	Proportion of immigrants with university degree (region)	2.78 (3.19)
Market contextual factors (direct effect)	*Competition*	Herfindahl index (sector and region)	-1.01*** (0.38)
	Demand	Exports (sector and region)	0.020*** (0.0062)
	Uncertainty	Volatility of financial credits (sector)	89.6 (101)
	Regulation	Proportion of opening + closing of firms (region)	0.67 (0.7)
Knowledge contextual factors (returns effect)	*Support of knowledge supply*	RD&D p.w * Academic publications	-0.38* (0.23)
	Sectoral spillovers	RD&D p.w. * Inno sector-region	-0.0067 (0.089)
	Spatial spillovers	RD&D p.w * Proportion immigrants with university degree	0.40** (0.18)
Market contextual factors (returns effect)	*Competition*	RD&D p.w * Herfindahl index	0.0072 (0.017)
	Demand	RD&D p.w.* Exports	0.000079 (0.00044)
	Uncertainty	RD&D p.w. * Volatility of financial credits	-31.6*** (11.3)
	Regulation	RD&D p.w. *Proportion opening + closing firms	0.055 (0.069)
		Year =2015	0.19*** (0.015)
		Year =2016	0.32*** (0.029)
		Missing dummy	0.100** (0.047)
		Constant	10.5*** (0.47)
		Observations	9,246
		R-squared	0.395
		Number of ID	3,489

Note: Standard errors are clustered at the sector-size level
*** p<0.01, ** p<0.05, * p<0.1

Figures

Figure 1: Conceptual Framework

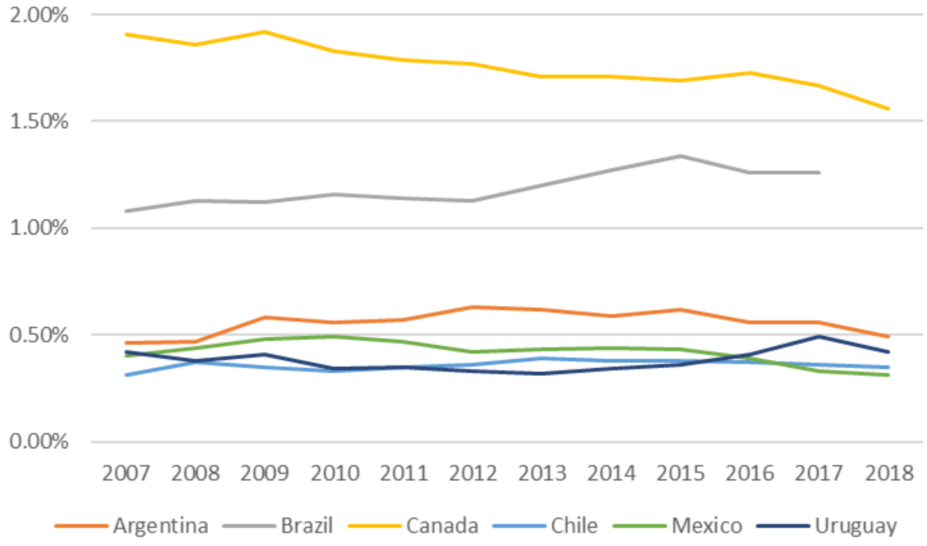


Source: Own elaboration.

Figure 2: Labour productivity per hour worked in 2019 (USD) and cumulative growth rate 1999-2019

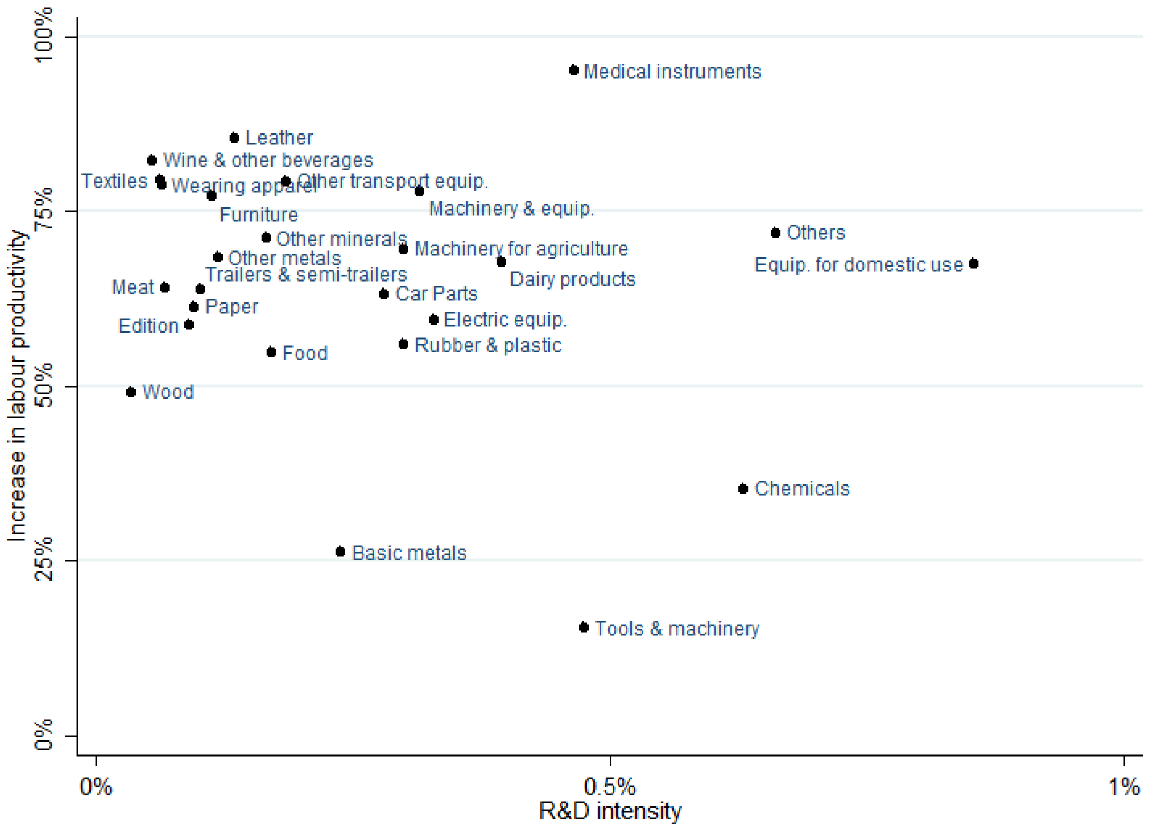
Source: Own elaboration based on data from The Conference Board Inc.

Figure 3: R&D expenditures (% of GDP)



Source: Own elaboration based on data from RICyT (Red de Indicadores de Ciencia y Tecnología Interamericana e Iberoamericana) http://www.ricyt.org/en/category/indicators/.

Figure 4: Increase in labour productivity and R&D intensity by industry (2014-2016)



Note: Increase in labour productivity = 2014-2016 increase in industry value added over total industry employment; R&D intensity = total industry expenditure in internal R&D over total industry sales (2014-1016 average). Pharmaceutical industry has been excluded for visual purposes as it is a positive outlier in R&D intensity.
Source: Own elaboration based on ENDEI 2 (2014-2016).

Figure 5: Dispersion of sectoral and regional contextual factors

Figure 5a: Immigrants with university degree

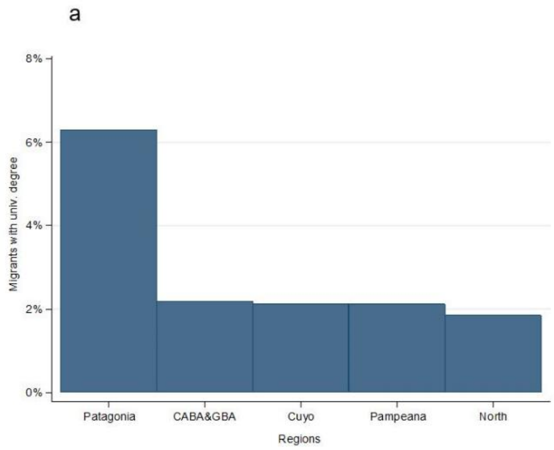
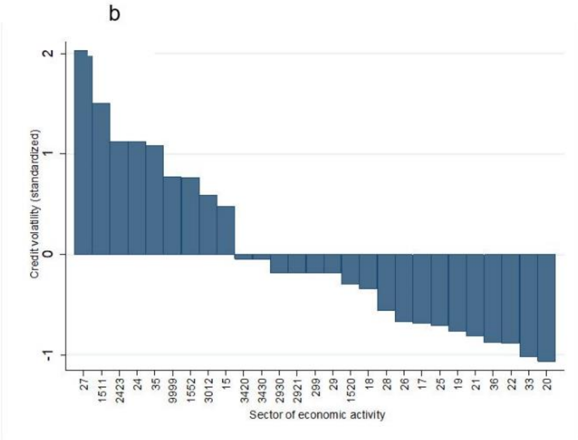
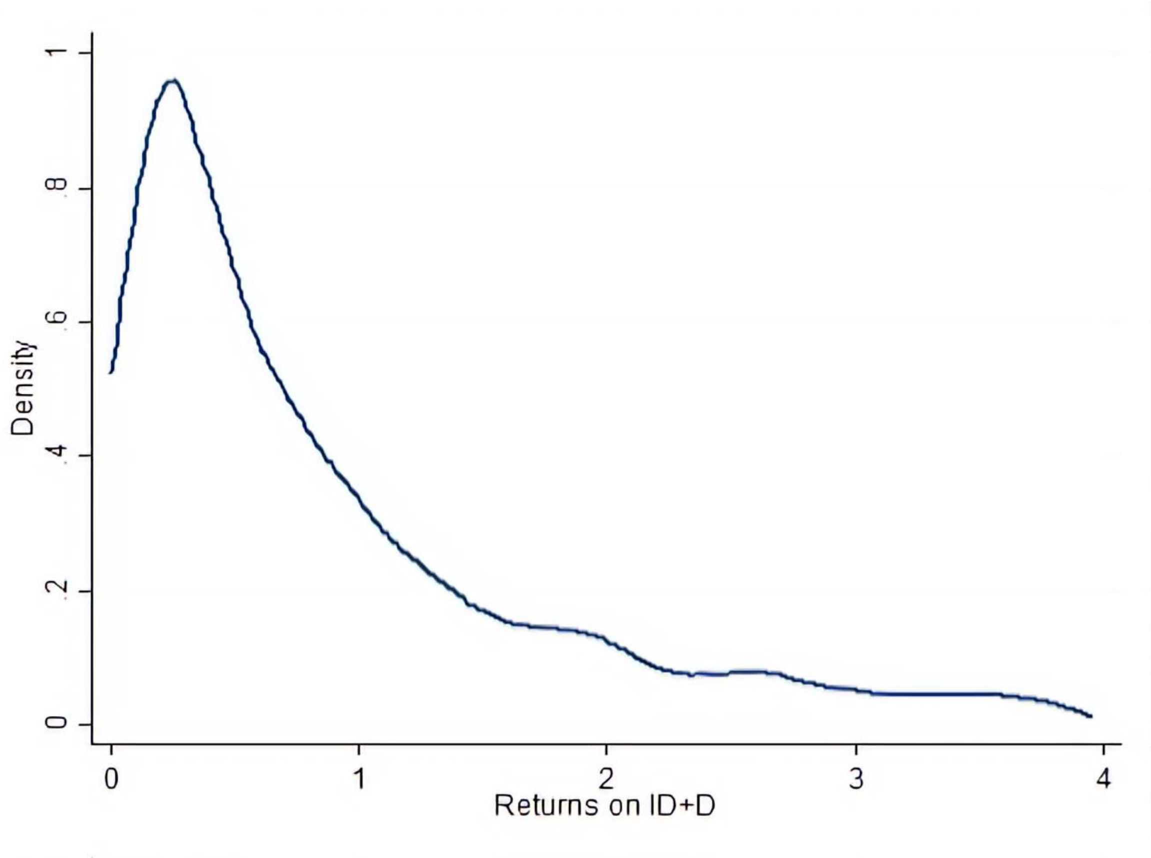


Figure 5b: Sectoral financial volatility



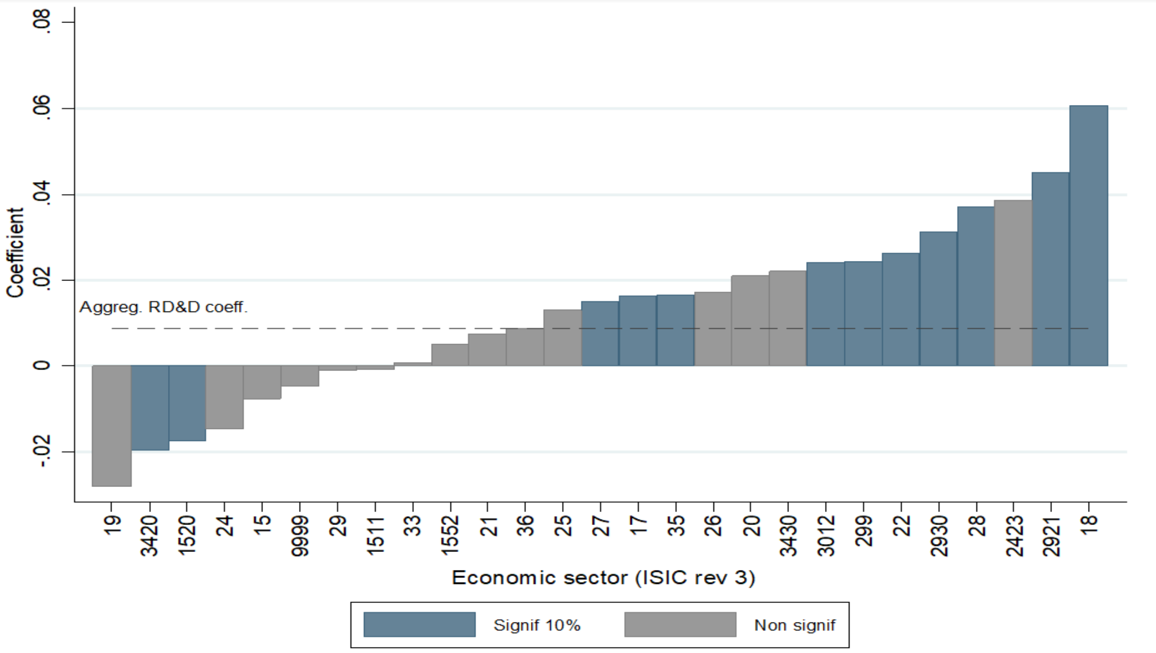
Source: Permanent household survey (EPH) and Argentina Central Bank databases.

Figure 6: Kernel density of Returns to RD&D in monetary units



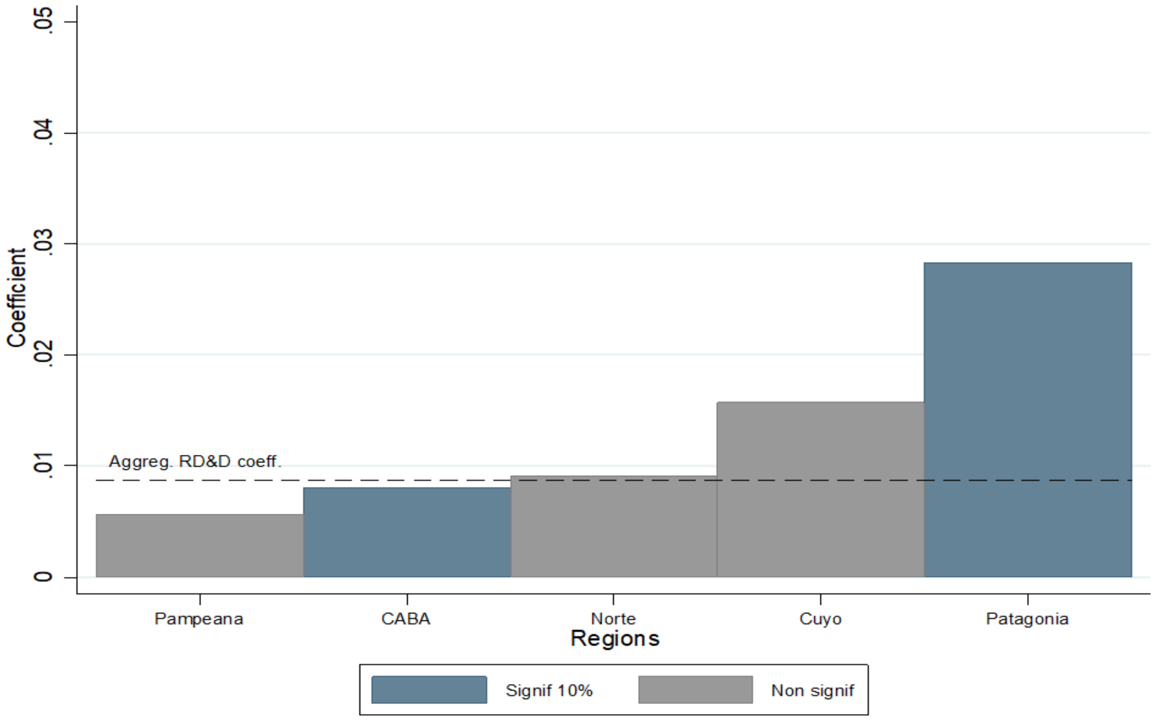
Note : The returns to RD&D in monetary units for each firm are calculated as $\hat{\delta}\frac{\widehat{va_{it}}}{i_{it}}$ from equation [1] (i.e. the percentage increase in value added per worker per 1% of increase in RD&D per worker multiplied by the mean of the fraction between the estimated VA per worker and RD&D per worker across 2014-16). Firms with zero investment in RD&D are not included in the distribution. Graph shows up to 90th percentile of the distribution.
Source: Own elaboration based on ENDEI 2.

Figure 7. Estimated coefficients for sectoral returns to RD&D, 2014-2016.



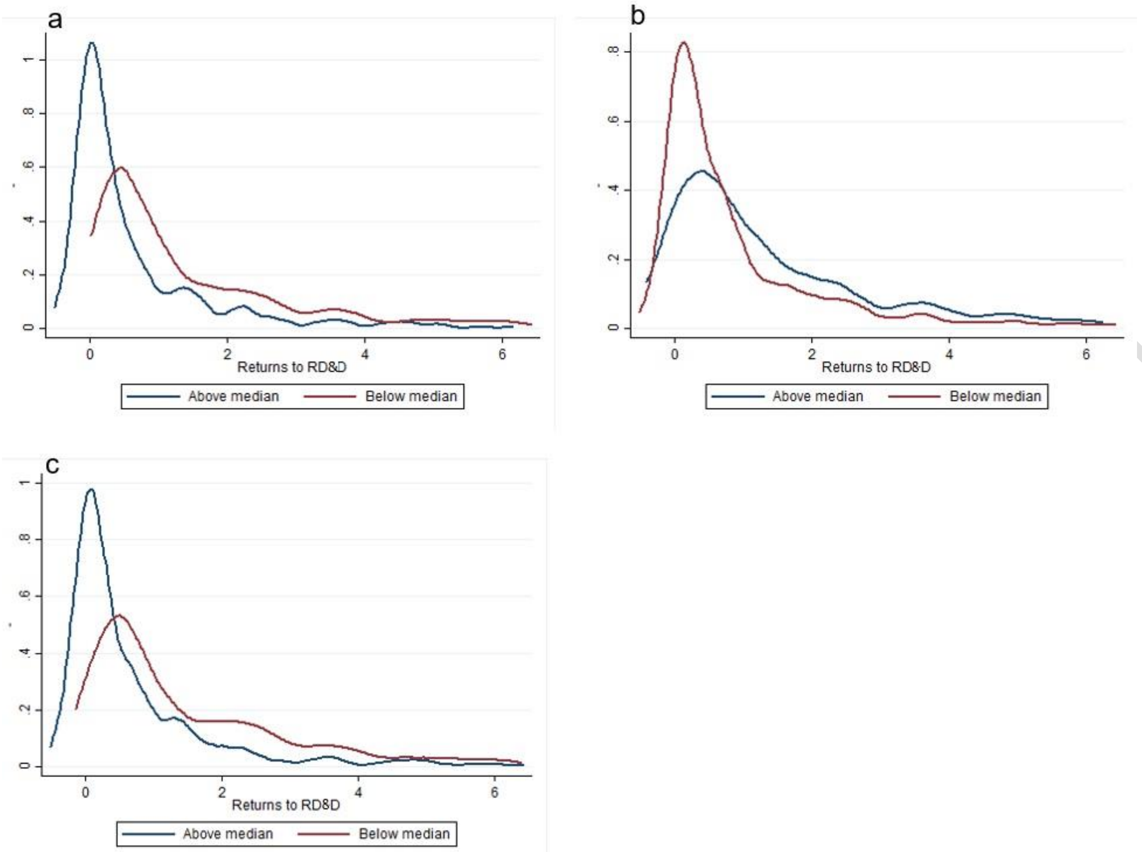
Source: Estimated coefficients of equation [1] by sector, using ENDEI 2.

Figure 8. Estimated coefficients for regional returns to RD&D, 2014-2016



Source: Estimated coefficients of equation [1] by region, using ENDEI 2.

Figures 9: Kernel density of returns to RD&D in monetary units split by the median of contextual factors.



Note: the returns to RD&D in monetary units for each firm are calculated as in Fig. 6 but using estimates from equation [2]. Panel (a) Support of knowledge supply, panel (b) Uncertainty and panel (c) Spatial spillovers.
Sources: ENDEI 2 and those included in Table A.1 in Appendix A for contextual factors.

Figure captions

Figure 1: Conceptual Framework

Figure 2: Labour productivity per hour worked in 2019 (USD) and cumulative growth rate 1999-2019

Figure 3: R&D expenditures (% of GDP)

Figure 4: Increase in labour productivity and R&D intensity by industry (2014-2016)

Figure 5: Dispersion of sectoral and regional contextual factors

Figure 6: Kernel density of Returns to RD&D in monetary units

Figure 7: Estimated coefficients for sectoral returns to RD&D, 2014-2016

Figure 8: Estimated coefficients for regional returns to RD&D, 2014-2016

Figures 9: Kernel density of returns to RD&D in monetary units split by the median of contextual factors