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Explaining Differences in the Returns to R&D in Argentina

The Role of Contextual Factors and Complementarities

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Abstract

Argentina's private investment in research and development is well below that of its peers. One important reason may be low and very heterogeneous returns to research and development activities on productivity. This paper uses novel microdata to estimate the returns to research and development and understand the contextual factors that shape their heterogeneity. The paper groups these context-based factors into knowledge complementary factors (that is, factors that affect the returns via learning capabilities from external sources of knowledge) and market complementary factors (factors that act via business capabilities to appropriate the returns to research and development investments). The paper hypothesizes that the effects of contextual factors depend on firms' management capabilities and attitudes (innovative capacity), which determine firms' ability to benefit from the context. The findings suggest that the returns are indeed heterogeneous across regions and sectors, and these results depend on some context-based factors, which can boost or depress the returns to R&D. The results have important policy implications, considering the effectiveness of innovation policies, need for adapting to specific regions and sectors, and maximization of the impact of these factors on the returns to research and development.

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Explaining Differences in the Returns to R&D in Argentina: The Role of Contextual Factors and Complementarities [1]

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1. Motivation

Investments in knowledge capital and other activities related to innovation are considered a key enabling factor in the catch-up process, in terms of both scaling up the technological ladder and promoting 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 about the relation between investments in innovation, productivity, and economic growth. Evidence on this relation has been produced at the macro, sectoral, and micro levels: see, for example, Teixeira and Queirós (2016) (macro level); Strobel (2012) (sectoral level); and Crespi and Zuniga (2012) (micro level).

The creation of new knowledge that supports innovation is a cumulative process. Thus, past performance has an important influence on firms' knowledge efforts and subsequent performance. Because the past matters, various structural characteristics (such as size, age, region, and sector) can be expected to influence different patterns of investment in innovation. In addition, the effectiveness—the returns—in which investments in innovation are converted into productivity or sales growth can also vary (Fung 2004, Marín and Petralia 2018). For example, one peso invested in R&D in wine production in the Mendoza region may not enhance productivity in a similar way to one peso invested in R&D in wine production in the Bordeaux region, because the knowledge, framework conditions, access to inputs, and market context are different, creating distinct opportunities in complementing private efforts in R&D.

In other words, investment in knowledge is not directly transmitted into performance (Ngai and Samaniego 2011). It depends on the particular circumstances in which investment takes place. Every context offers a different array of complementary factors that are needed to make the most of internal efforts. Whether or not several of these factors are present and the extent to which they do or do not complement one another may alter the returns to innovation.[3]

In addition, returns to innovation may differ in relation to firm-level heterogeneity. Acemoglu et al. (2018) use the term "innovative capacity" to describe those micro-level attributes that result in different R&D performance among firms. Cirera, Maloney, and Sarrias (2019) suggest that some of this heterogeneous innovative capacity in transforming knowledge investments into productivity gains is related to the quality of managerial practices. These firm-specific characteristics may affect the degree to which the firm is able to benefit from its context (that is, how sensitive it is to the factors previously mentioned). Hence, this paper suggests that these firm-level management attributes may interact with contextual factors, increasing the heterogeneity of R&D returns among firms.

[3] The existence or lack of key contextual factors can affect the returns to R&D. What strictly speaking makes them complementary or not is whether the effect on productivity is larger when these factors and R&D are present at the same time—the final impact on productivity is larger than the sum of the individual effects.

Heterogeneity in the returns to R&D activities is of paramount importance for policy. Firms are expected to invest more in those innovation activities that yield positive returns; in other words, if the returns are low, as in the case of many developing and middle-income countries (Goñi and Maloney 2017), it is unlikely that firms will invest in innovation activities. Policies that aim to encourage investments in R&D but cannot affect these returns will fail, especially in sectors and regions with low returns. Therefore, understanding what factors explain these low returns and the heterogeneity in attaining them is critical for policy design and effectiveness.

In this paper, we examine the hypothesis that several contextual factors determine both the set of technological possibilities and the probabilities the innovation will succeed (in terms of higher productivity), as well as firms' capacity to appropriate the rewards of innovative investments in their production process. We call these factors, respectively, *knowledge complementary factors* and *market complementary factors.* We also hypothesize that the impact of these complementary factors is mediated by the firm's innovative capacity, which is manifested in specific management strategies that can maximize the returns when these complementary factors are available.

This study contributes to previous literature because it is the first to empirically analyze the relationship between contextual factors and R&D returns in Argentina with micro-level data in a comprehensive set-up.[4] In Argentina, firms' context is frequently mentioned as an important factor incentivizing firms' defensive or short-term low-risk strategies, instead of pursuing longer-term innovative strategies that could boost productivity levels (Katz 2000, Katz and Bernat 2011, Arza 2013, Kosacoff 2000, Chudnovsky 2001, Fanelli 2002). The novelty of our approach lies in the comprehensive evaluation of this hypothesis in an econometric framework. This allows us to estimate the relationship between innovation returns and the context dimensions (which we group into "knowledge" and "market" factors), while also considering firm-specific innovative capacity. In addition, this is one of the first papers that uses data from the second wave of the Employment and Innovation Dynamics National Survey (known as ENDEI, for its Spanish acronym) (ENDEI 2014–2016). By merging ENDEI data with contextual characteristics defined at the sectoral and/or regional level,[5] this paper also improves data availability by creating a novel and original database that could be useful for future studies.

The remaining of this paper is organized as follows. Section 2 describes the Argentinean context and its R&D and productivity performance to motivate the discussion. Section 3 describes the conceptual framework used. Section 4 describes the methodology and data. Section 5 presents results of the estimation of the production function. Section 6 concludes by offering policy recommendations, suggesting lines for future research, and discussing implications for data collection. The appendixes provide supplemental data and analysis.

2. The Argentinean Context

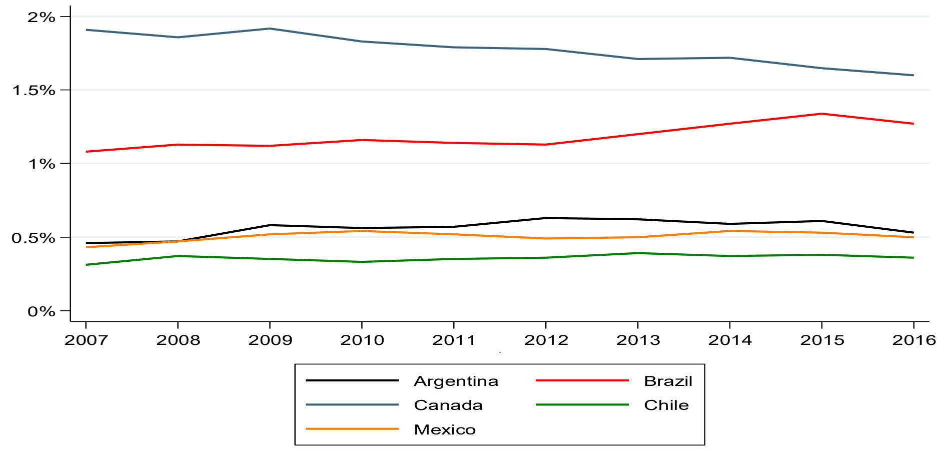
Although Argentina's expenditure on R&D relative to GDP or in US dollars per capita is much lower than that in developed countries, it is higher than that in regional peers, with the exception

[4] At the macro level, the potential impact of these complementarities has been explored in, for example, Klenow and Rodriguez-Clare (2005), Maloney and Rodríguez-Clare (2007), and Goñi and Maloney (2017)—but not specifically for Argentina. These studies stress the importance (or the lack) of these complementary factors in explaining differences in the returns of R&D across countries and in the distance to the technological frontier.

[5] This database was built using a variety of different data sources, each originally with different levels of disaggregation. Details are presented in appendix A, table A.1.

of Brazil (see figure 1).[6] Argentina has increased the amount of resources committed to R&D over the past few years. Between 2007 and 2016, Argentina increased its total expenditures in R&D by 78 percent—measured in current US dollars in purchasing power parity (PPP) terms—and its R&D/GDP ratio by 15 percent (from 0.46 percent to 0.53 percent). These levels of growth are similar to Chile (16 percent), Mexico (16 percent), and Brazil (18 percent).

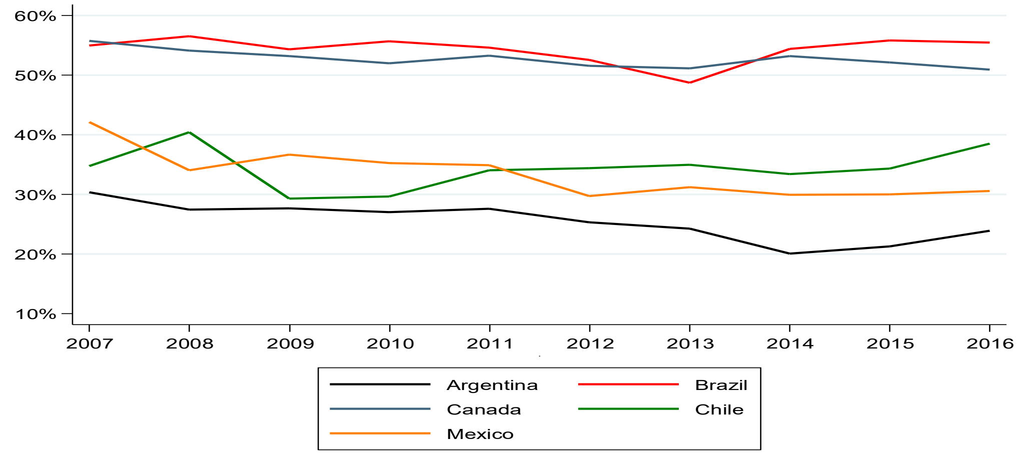
Figure 1. R&D Expenditures, Argentina and Comparators, 2007–16 (percent of GDP)



Source: RICYT

However, Argentina lags behind regional peers in private R&D expenditures (figure 2) and does not seem to be catching up. The share of private R&D expenditures in total R&D expenditures fell by 21 percent between 2007 and 2016, reaching a level of merely 24 percent of total R&D. This suggests a large preponderance of public R&D in total innovation investments in Argentina, larger than in peer countries—and potentially the result of low returns to R&D in private enterprises.

Figure 2. R&D Expenditures by Firms, Argentina and Comparators, 2007–16 (percent of total R&D)

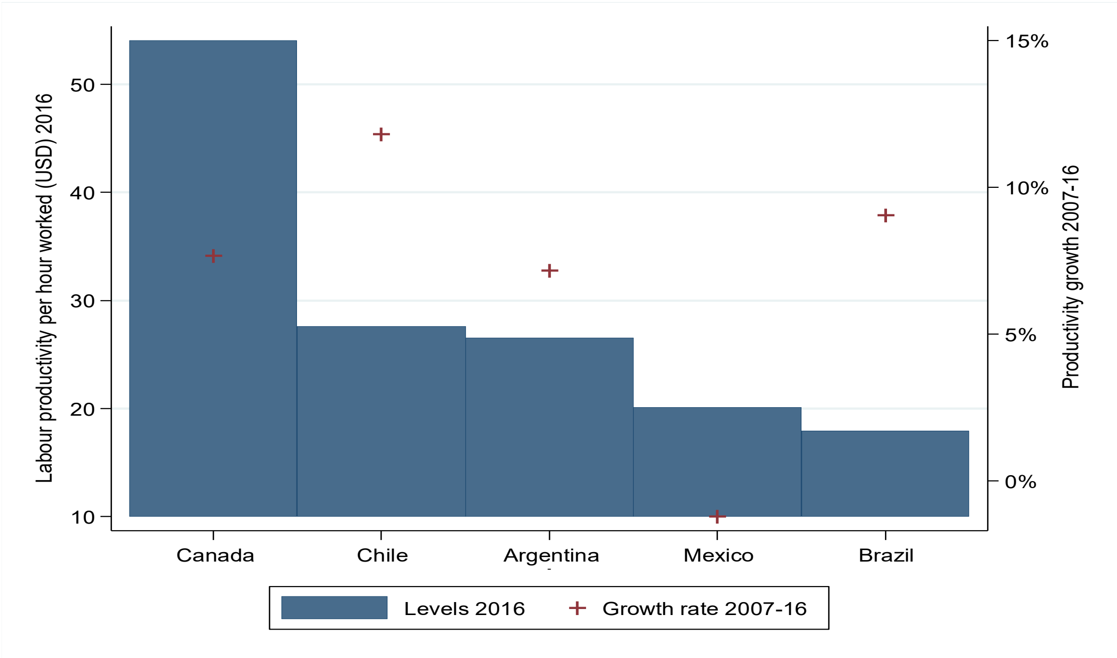


Source: RICYT

[6] Figures 1 to 3 contrast indicators on R&D and productivity in Argentina with a series of comparable countries. For these comparisons, we include one recent high-income country (Chile), two large Latin America economies (Brazil and Chile), and two countries belonging to the Organisation for Economic Co-operation and Development (OECD) (Canada and Chile).

In terms of labor productivity, Argentina's performance is similar to Chile's and better than Brazil's and Mexico's (figure 3), but falls within the low labor productivity growth characteristic of the last two decades in the region. Argentina's labor productivity increased by 7 percent between 2007 and 2016 but lagged behind Brazil (9 percent) and Chile (12 percent). These figures suggest that innovation investments, especially in the private sector, are not sufficient and/or effective enough to have an impact on the much-needed productivity growth. In addition, the fact that the ratio of labor productivity to R&D expenditures fell by 40 percent in Argentina but only by 30 percent in Brazil between 2007 and 2016 suggests that there might be room for improving the profitability of expenditures on R&D.

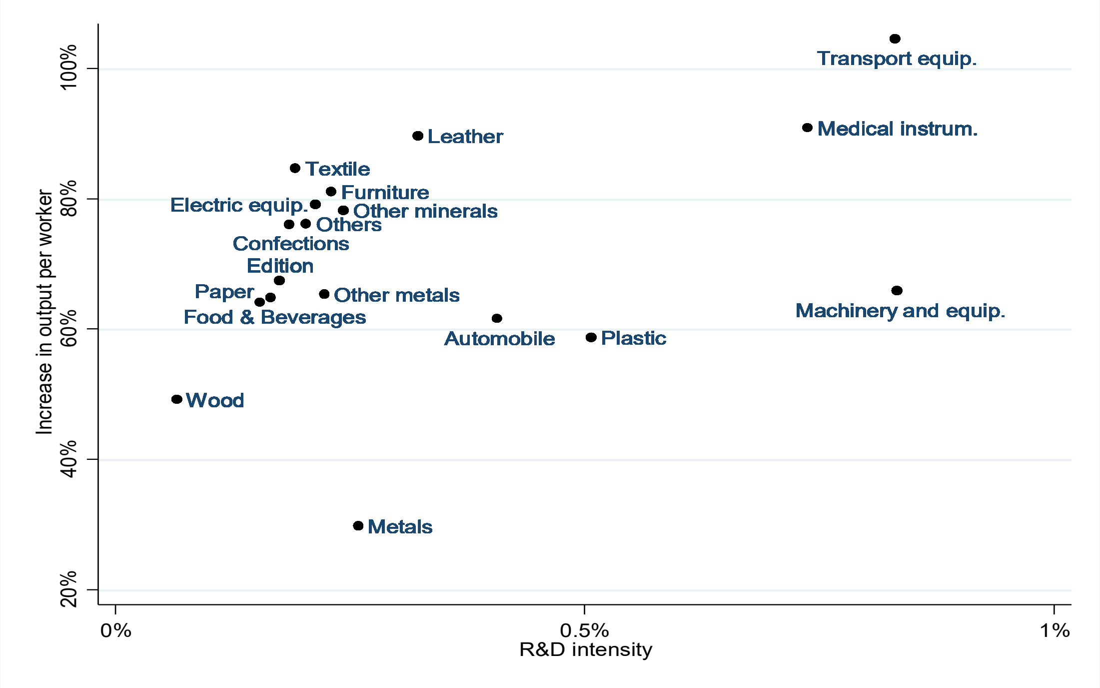
Figure 3. Labor Productivity, Argentina and Comparators, 2007–16



Source: The Conference Board Total Economy Database.

To fully benefit from increases in R&D expenditure and encourage private participation, it is important to identify possible inefficiencies in the role of knowledge in the production function, which might be deterring the contribution of R&D to labor productivity. In fact, when we compare R&D intensity and increases in labor productivity by sector, we do not always find the positive relation we would expect. Some sectors have high levels of R&D intensity but low productivity growth and vice versa (figure 4). In addition, an important share of firms manage to become innovators without committing any investment resources or by doing so very sporadically (Suárez, Lugones, and Moldovan 2008). This suggests that these firms are either taking advantage of their contextual environment—for example, through imitation, or linking to science and technology (S&T) organizations, or by employing skilled personnel who had worked previously in other innovative firms—and/or through the type of innovation that is very incremental and does not require any formal R&D efforts, but only imitation and technological adaptation or adoption.

Figure 4. Increase in Labor Productivity and R&D Intensity by sector, Argentina, 2014–16



Source: ENDEI 2014–2016.
Note: Increase in output per worker = 2014–16 increase in value added over total employment; R&D intensity = expenditure in internal R&D over sales 2014–16.

In sum, aggregate data from Argentina suggest there might be important inefficiencies in the role of knowledge in the production function, reducing private investments in R&D and constraining the impact of knowledge investments on productivity. This poses the question of what role the lack of key complementarities plays in the effectiveness of innovation investments and their returns. In other words, what is the role of knowledge complementary factors and market complementary factors in pushing upward or holding back the returns to private investment in innovation and what could the firm do to make the most of those factors?

3. Conceptual Framework

The relationship between innovation and firm performance has been largely studied, primarily using the extended knowledge production function approach pioneered by Griliches (1979). A key element in the estimation of production functions is the need to control for the endogeneity of investment (in knowledge stocks or physical capital stocks) and productivity (Parisi, Schiantarelli, and Sembenelli 2006, Doraszelski and Jaumandreu 2013, Harrigan, Reshef, and Toubal 2018, Siliverstovs 2016).

With the expansion of Community Innovation Surveys (CIS) in the European Union (EU)—and later in other countries—Crépon, Duguet, and Mairesse (CDM) proposed a framework (Crepon, Duguet, and Mairesse 1998) that models the interdependent relation between investment in R&D, innovative outputs, and firms' productivity. This framework has been estimated in several contexts, including developing countries.[7] Although this literature has reached consensus on the relevance of investments in innovation in terms of firm upgrading, there is less clarity about what factors affect the rate of return.

When trying to understand what factors affect these returns, it is very important to consider the systemic nature of innovation. In this view, innovation is considered to be the result of the interaction of many socioeconomic actors whose behaviors cannot be separated from other contextual characteristics, such as regulations, social norms, political values, and collective priorities (Lundvall 1992, Nelson 1993). This approach focused initially on innovation at the national level, through so-called National Innovation Systems, but later expanded to consider the concept of *systems of innovation* at regional levels (Cooke 2001, Cooke, Uranga, and Etxebarria 1997) and sectoral levels (Malerba 2002). The bottom line of this literature is that external knowledge boosts firms' *learning capabilities*, which, in turn, positively affect the return of private investment in innovation.

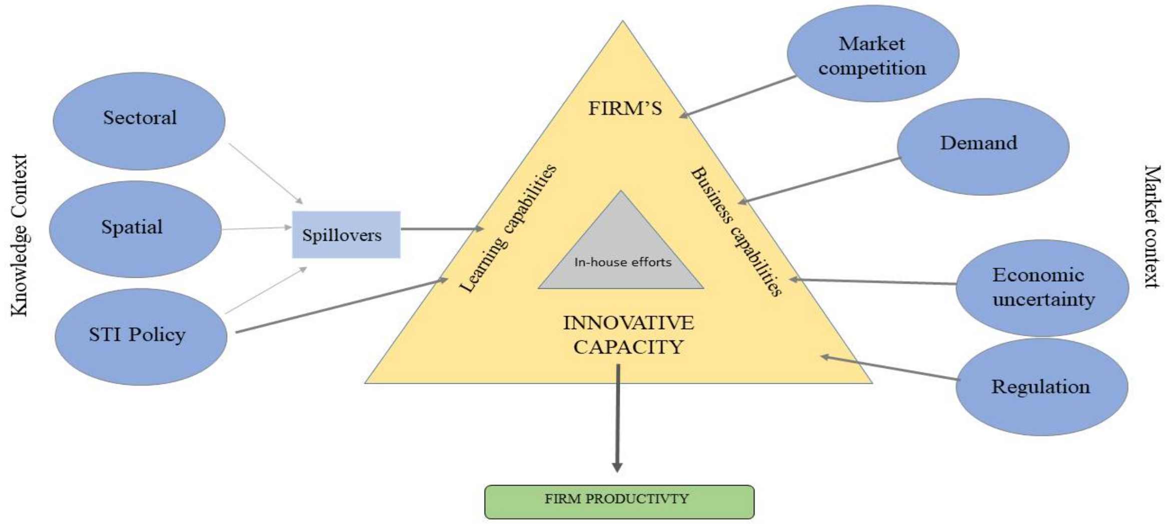
In addition, a more scattered literature analyzing macro-micro linkages on innovation also provides some insights on what factors could affect firms' returns to R&D through their capacity to convert opportunities into economic rewards (that is, how they could enhance firms' *business capabilities*). This strand of literature has examined how productivity or innovation reacts to macroeconomic uncertainty (Bernanke 1983, Bloom 2009, Acemoglu et al. 2003); competition (Aghion et al. 2005); institutional quality (Acemoglu 2003); and demand-pull factors (Adner 2002).

In this paper, based on the *knowledge expanded production function*, we bring together different contributions from these strands of literature, including qualitative insights, to analyze the role of contextual complementary factors and firms' capacity to enhance the returns of investment in innovation. We organize this body of literature into three groups: those studies that discuss contextual aspects that enhance firms' technological learning capabilities (that is, knowledge complementary factors); studies that discuss the role of contextual factors affecting firms' capacity of doing business or fully appropriating the rewards of their assets (that is, market complementary factors); and studies discussing the role of micro heterogeneity in taking advantage of contextual opportunities (that is, firms' innovative capacity).

[7] Jefferson et al. (2006) used panel data from China to estimate the impact of R&D in terms of productivity and profitability. The paper establishes a lag structure to offset simultaneity biases and correct for endogeneity. It finds that R&D has positive effect on both profitability and productivity. Antoncic et al. (2007) used a structural equation framework on cross-sectional data for Slovenia and Romania to test a hypothesis about the positive impact of organizational support and alliances on innovativeness and, in turn, a positive impact of innovation on firms' performance (measured by growth, profitability, and wealth). They find empirical support for their hypotheses. Benavente (2006) applied an adapted version of the CDM framework using Chilean cross-section data. They find that neither R&D nor innovation results (share of sales of new products—so-called 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. In addition, 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 World Bank Enterprise Survey 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 translates into a strong increase in labor 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 show that investment in R&D boosts firms' labor productivity.

Figure 5 summarizes the key elements identified by different strands of the literature.

Figure 5. Conceptual Framework



Note: STI =science, technology, and innovation.

3.1. Knowledge Context

The first strand of literature investigates why some industries and regions are more dynamic than others. Studies generally attribute dynamism (or lack to dynamism) to the intrinsic characteristics of technological regimes, and systemic aspects of science, technology, and innovation (STI). These complementary factors are normally measured at the meso (sector/region) level and could be largely considered to be exogenous factors molding firms' patterns of innovation. We organize this literature into two blocs according to how these factors interact with firms' *learning capabilities.*

On the one hand, there is a vast literature on knowledge spillovers: several aspects have been identified at the regional or sectoral level that boost firms' learning capacity through their access to external knowledge. On the other hand, there is the literature assessing the contribution of STI policies in enhancing firms' absorptive or innovative capabilities, designed either to increase the likelihood of knowledge spillovers (such as investing in developing knowledge consortiums) or to boost firms' innovative capacities directly (such as training programs, technical assistance, and financing infrastructure).

3.1.1. Spillovers

In the systemic approach, learning by interaction plays a key role in boosting firms' learning capabilities through their access to external knowledge, embodied in other organizations or individuals. Roper and Love (2018) propose three mechanisms through which external knowledge could be privately appropriated: (i) active interaction, as in university-industry linkages or client-provider knowledge linkages, or other voluntary knowledge linkages, which could be more or less formal; (ii) active–non-interactive, as in imitation, reverse engineering, or access to codified knowledge; and/or (iii) knowledge externalities, as in social networks, which in turn positively affect the return of private investment in innovation. In this work, we refer to positive *spillovers* on firms' productivity that are originated by knowledge-related activities carried out by other organizations or individuals in their immediate context. These spillovers can be sectoral or regional/spatial.

a) Sectoral context

The literature on *technological opportunities* (TO) argues that the sectoral differences in the returns to R&D are explained by variations in TO. These are defined as the set of technological options that determine the distribution of the values of the production function or product attributes that can be achieved via R&D (Klevorick et al. (1995)). Although this concept is fundamentally technologically driven, the preoccupation with decreasing returns of investment in R&D pushes scholars to analyze systemic sources claimed to be able to renew the pool of TO. These are explained either by technological trajectories—as in the traditional literature arguing that technological specificities drive different patterns of innovation across sectors (Malerba and Orsenigo 1995, Pavitt 1984)[8]—or related to spillovers created either by –STI policy (particularly in 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 later contributions, including Marín and Petralia (2018); Fung (2004); and Kafouros and Buckley (2008).[9]

b) Regional/spatial context

Several contributions concerning the systemic approach come from regional innovation studies analyzing how socioeconomic factors present in the territory where the firm produces (such as the institutional capacity, the supply of human capital, and public support for the generation of knowledge) affect both the level and the effectiveness of their investment in R&D (Crescenzi and Rodríguez-Pose 2013). This literature is motivated by the stylized fact that innovation is not randomly distributed in the territory but tends to concentrate geographically (Audretsch 1998). As far back as 1890, Marshall (1890) identified three reasons that explain geographical concentration: availability of skilled workers; availability of specific inputs, such as natural resources; and technological spillovers. This rationale gave birth to the new economic geography and the study of economics of agglomeration, led by Krugman (1991). According to his studies, "geographic concentration of production is clear evidence of the pervasive influence of some kind of increasing returns" (page 6).

3.1.2. Science, Technology, and Innovation Policies

Policy instruments are designed to strengthen several aspects needed to increase the rate of return of R&D, such as a supportive scientific system; providing infrastructure for interaction

[8] Pavitt (1984) classifies industries according to the source of technology (such as inside/outside the firm, government/private-financed); users' needs (such as price/performance); and methods used to appropriate benefits from innovation (such as secrecy, patents, time lags, and unique knowledge). Similarly, Malerba and Orsenigo (1995) explore the dynamics of technological change and define two different groups, labeled technological regimes, that are 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.
[9] Another important related strand of literature summarized in Griliches (1994) and more recently in Bloom et al. (2017) focuses on the productivity of new ideas. This literature is more macro but has sector-specific implications because in some sectors ideas "are harder to get" and this will affect their returns to R&D investments to develop them.

and learning; supporting adequate financing schemes to tackle technical challenges; addressing market failures and/or guiding market signals to reflect and internalize the social returns to innovation; building an institutional (regulatory) environment to promote certain strategic innovation paths; and/or guiding the generation of opportunities and promoting interactions between the actors sharing that vision of development (OECD 1998).

Innovation policy also has a key role in creating 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). Whether all or some of these aspects do or not exist affects the effectiveness of any private effort in innovation. STI policies, therefore, are a *complementary factor*, mostly affecting firms' *learning capabilities* but also affecting firms' *business opportunities*. For example, regulatory aspects of STI instruments such as intellectual property schemes, or specific instruments such as public procurement, grants, or other monetary incentives, could improve the rewards to innovation, and therefore STI policy, thus also constituting an important *market* complementary factor (included in the Regulation segment in figure 5).

3.2. Market Context

While traditionally the National Innovation System literature has emphasized the systemic nature of innovation and the importance of key complementary factors and institutions in defining innovation outcomes, it has often lacked clarity on what context factors matter and are complementary to R&D. Maloney (2017) proposes where to set the boundaries of the NIS while emphasizing the often underacknowledged role of barriers to accumulation of factors of production. In the context of a knowledge production function, knowledge inputs are often affected by barriers that deter the accumulation of other factors: that is, barriers to capital investment due to uncertainty or financial market imperfections are also barriers to invest in knowledge capital. A key insight is that in addition to the knowledge context, key aspects of the traditional market context will also have an impact on the returns to investment in innovation.

3.2.1. Competition

Market competition has been considered an important aspect promoting or deterring innovative behavior. There is general consensus about the simultaneous determination of market competition and innovation. The concepts of creative destruction and creative accumulation in Schumpeterian approaches are evidence of an awareness of this simultaneity. In a regime characterized by creative destruction, entrepreneurs are driven by fear of others innovating first. 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.[10] Thus, market competition may affect both incentives to invest and opportunities to appropriate rewards from such investment, which makes it a central market complementary factor.

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

3.2.2. *Demand*

A similar argument could be made in relation to market demand. There is a long tradition in innovation studies highlighting the role of demand in pulling technological progress, often based on Kaldor's ideas about the importance of demand 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, Kaldor 1966, McCombie and Thirlwall 1995, Schmookler 1962). Demand-pull factors have since been considered key aspects of guiding investment in innovation and explaining heterogeneity in return rates. In turn, lack of demand or uncertainty about future demand are considered deterrents to firms' decisions to innovate (see, for example, García-Quevedo, Pellegrino, and Savona (2016)).

3.2.3. *Uncertainty*

The issue of economic uncertainty in general requires specific consideration as a condition that could affect market and learning opportunities and therefore firms' attainment and appropriation of innovation rewards. A large array of studies analyzes the negative impact of uncertainty on investment due to the existence of irreversibility.[11] A firm has more flexibility to decide between inputs, technologies, and organizational set-ups before it makes the decision to invest in a particular machinery or to initiate a specific R&D project. Then, if relevant variables (such as interest rates, asset prices, exchange rates, input prices, and labor costs) are uncertain, 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. The acquisition of knowledge is not automatic, and learning requires foresight over the medium term. Thus, when a context is highly uncertain and macroeconomic changes cannot be fully anticipated, investment behavior will be limited and contemporaneous rewards on past investments will be reduced, which justifies our consideration of uncertainty as a *market complementary factor*.[12]

3.2.4. *Regulations and Business Environment*

Several policy regimes, such as labor, tax, trade, foreign direct investment, and/or competition policy, affect knowledge investment decisions and their impact. For example, the ability to hire engineers and move across tasks in the plant, import machinery, or hire foreign managers affect the effectiveness of R&D. More generally, the regulatory and business environment affects the incentives to invest in innovation activities and the returns to these investments in general. This therefore also makes it an important *market complementary* factor.

[11] 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 focus on US manufacturing industries, while Pindyck and Solimano's contribution is a cross-country study. Indeed, they find that the impact is larger for developing countries (see Pindyck and Solimano (1993): 33).

[12] Given that a less uncertain environment also favors learning, as discussed, innovative capacity could also be considered a knowledge complementary factor.

3.3. Innovative Capacity

Firms' ability to transform knowledge investments into productivity gains also varies. The bottom line of this strand of literature is that there are differences in firms' innovative capacity that translate into heterogeneity in performance.[13]

This heterogeneity is also likely to mediate the impact of the context and potential complementary factors already discussed. STI support for example, is likely to be effective for firms with greater innovative capacity. Similarly, more innovative firms are more likely to take advantage of a good supply of engineers and better demand conditions or locational spillovers.

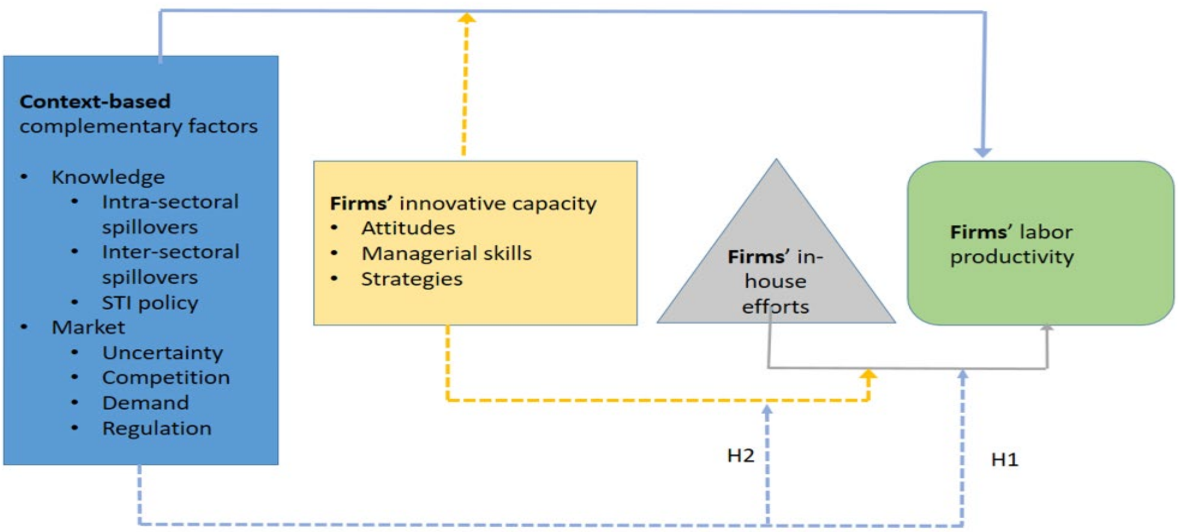
In sum, our conceptual framework anticipates that there are knowledge and market factors stemming from the firms' context that complement private investments in knowledge capital. In addition, some firms are better prepared to take advantage of those factors. All in all, the existence of context-based factors and firms' innovative capacity to make the most of them could explain significant heterogeneity in returns. We therefore propose two hypotheses regarding the role of context-based factors on returns to private investment in innovation (against the null hypothesis that context-based factors do not matter for returns to innovation).

H1: Context-based factors directly affect the returns to in-house investment in innovation.

H2. Context-based factors affect the returns to in-house investment in innovation when mediated by firms' innovative capacity.

These hypotheses are summarized in figure 6. Our goal in the sections that follow is to empirically identify the key factors that may, according to H1 and H2, affect R&D returns in Argentina, with the aim of improving policy design.

Figure 6. Main Hypotheses under Study



[13] Acemoglu et al. (2018) emphasize that some of the distortions can be associated with industrial policy. Public support to firms that have low quality of innovation—firms with little ability to convert innovation investments into productivity— will result in lower productivity gains and as a result lower aggregate returns.

4. Methodology

4.1. Data Sources

Micro Data

The main database for our analysis is the second Employment and Innovation Dynamics National Survey (ENDEI 2). The use of this data set is completely novel. Access was granted to us by the National Directorate of Scientific Information (Dirección Nacional de Información Científica, DNIC) and the Under-secretariat of Studies and Prospective (Subsecretaría de Estudios y Prospectiva), specifically for the needs of this project.[14] This survey covers the 2014–16 period and was carried out jointly by the Labor and Employment Secretariat (Secretaría de Trabajo y Empleo) and the Science, Technology and Productive Innovation Secretariat[15] (Secretaría de Ciencia, Tecnología e Innovación Productiva). The sample was drawn to be representative of manufacturing firms with at least 10 employees, in terms of size (small, medium, and large firms), region (five geographical areas), and sector (mostly at the 2-digit ISIC level).[16] The sample includes 3,945 firms. For some exercises, we used the previous ENDEI (hereafter ENDEI 1), comprising 3,691 firms, which covers the period 2010–12 and which is representative at the size and sectoral level. We could not use panel data because both waves were not matched at the firm level.[17]

The ENDEI has two structured questionnaires, one self-administered and one that requires a face-to-face interview. The former contains questions that require inputs from different areas of the firm: income; expenses (such as wages and salaries, intermediate consumption, and investment in fixed assets);[18] employment (according to hierarchies and qualification); and remuneration and spending in innovation activities (such as R&D, consultancy, and acquisition of machinery and equipment). The latter contains mainly qualitative information on several issues regarding innovation and employment dynamics: organizational capability and business

[14] We were allowed access to this information with an agreement in 2019 between the World Bank and the Ministry of Production and Labor (Ministerio de Producción y Trabajo). The database was completely anonymized and prepared specifically for the needs of this paper. In order to respect the confidentiality agreement with the firms surveyed, we worked with a computer in the offices of the DNIC, under constant supervision of the team.

[15] The former Ministry of Science and Technology, which was transformed into a Secretariat in September 2018. At the end of 2019, the institution returned to a Ministry structure again.

[16] ISIC, the International Standard Industrial Classification of All Economic Activities, is the international reference classification of productive activities. The following sectors are included in this study: Food, beverages and tobacco; Chemicals and petrochemicals; Pharmaceutical; Basic metals; Motor vehicles, ships and other transport equipment; Paper and publishing; Rubber and plastic; Machinery and equipment; Textiles and wearing apparel; Electrical machinery and apparatus, TV and radio equipment; Wood and products of wood; Leather and footwear; and Other industries. For some sectors of special interest, information was disaggregated at 4 digits (Food and beverages; Chemicals; Machinery and equipment and Motor vehicles). The five regions were: Patagonia (including the provinces of Chubut, Neuquén, Rio Negro, Santa Cruz and Tierra del Fuego); Cuyo (including the 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.

[17] However, it is worth highlighting that 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 because ENDEI 1 is not representative at the regional level.

[18] Unfortunately, neither information for energy consumption nor investment in physical assets was correctly measured in ENDEI 2. Although those questions were included in the questionnaire, data were not made available because they include severe measurement errors. We needed to develop strategies to overcome these data constraints to estimate capital stock in the production functions, as discussed later in the paper.

strategy; innovation activities; profile of human resources dedicated to innovation activities; results of the innovation efforts; sources of information and innovation objectives; sources of finance for innovation activities; obstacles to innovation; linkages; employment management capabilities and training policy; organization of labor; and knowledge management capabilities.

Sectoral and Regional Data

Table A.1 of appendix A presents all indicators considered in the analysis as proxies of context-based complementary factors. They are organized according to our conceptual framework, presented in figure 5. These indicators were built from various data sources listed in the last column of the table.

4.2 Empirical Strategy

4.2.1 Introducing Innovation Complementarities in the Production Function

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]. Following Griliches (1979), this baseline equation is a production function in per worker units: that is, extended by knowledge. The dependent variable is the aggregate value[19] of firm i at year t. Inputs are labor (L), capital stock (C) and knowledge stock (I). We measure all variables in natural logarithms, assuming a log linear relationship between inputs and aggregate value. Firm and time fixed effects are included in order to control for firm and time invariant unobserved heterogeneity.

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

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

$$\frac{Y_{irst}}{L_{irst}} = \alpha + \beta L_{irst} + \gamma \frac{C_{irst}}{L_{irst}} + \delta_0 \frac{I_{irst}}{L_{irst}} + \delta_1 M_{rst} + \delta_2 K_{rst} + \delta_3 M_{rst} \frac{I_{irst}}{L_{irst}} + \delta_4 K_{rst} \frac{I_{irst}}{L_{irst}} + u_i + \tau_t + e_{irst}. \qquad [2]$$

Therefore, δ_0, δ_3 , and δ_4 are our main coefficients of interest because they estimate the marginal effect of market and knowledge complementary factors on innovation returns. Standard panel data procedures are used to produce estimates for coefficients.

4.2.2 Endogeneity of Investment in Innovation

The likely presence of omitted variables and simultaneity issues raises a challenge for the precise identification of the coefficients of the knowledge production function. In this section, we focus on the endogeneity of the investments in innovation variable, given that its returns over productivity are our main concern. We are aware that capital and labor variables are

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

probably also endogenous, but we do not take explicit measures with them because their returns lie beyond our research questions. Time and individual fixed effects, however, tackle issues of omitted variables for all independent variables, decreasing bias of all estimated coefficients.

Given that 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 know-how the firms' workers possess, or the quality of managerial capabilities could affect both firms' decisions regarding innovation and firms' productivity. In addition, while larger knowledge stocks may increase firm productivity, more productive firms are more likely to be exposed to 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.

We tackle time-invariant omitted variables—both observable and unobservable—by exploiting the panel structure of our data with the inclusion of firm and time fixed effects, as has been done in other papers using ENDEI survey databases (see, for example, Brambilla and Tortarolo (2018)). We also explore an instrumental variable (IV) approach to estimate the returns of R&D over productivity. Claiming exogeneity of variables coming from our own ENDEI database is questionable and the restrictions to merge other potential instruments from external sources at the firm level due to ENDEI's confidentiality issues limits our analysis. However, it is important to try to minimize potential biases due to the endogeneity. Next, we describe the IV strategy and present the best IV candidates. As we shall see, the instruments proposed are statistically strong and exogenous, but the results of the IV estimation differ sharply from those of our panel data estimation, which raises questions about the accuracy of the point estimates.

Our first IV candidate is a dummy variable on firm's *knowledge* about the existence of public support programs for innovation activities offered by the Ministry of Science and Technology (Ministerio de Ciencia y Tecnología). This variable has been implemented in previous empirical studies that use information from innovation surveys in Argentina (see, for example, Brambilla and Tortarolo (2018), de Elejalde, Giuliodori, and Stucchi (2011). The condition of relevance is expected to be fulfilled because firms that know about public programs are candidates to use it, and therefore have a higher investment in innovation activities. The exclusion condition is justified considering that this dummy variable measures *knowledge* about the program rather than firms' participation. The latter can be correlated with other variables that may affect firm´s productivity, given that the provision of public funds is sometimes based on firm performance. On the other hand, knowledge of the program greatly depends on public and private publicity for the program, which we can assume is random and uncorrelated with other firm characteristics.

Our second 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.[20] An essential reason for choosing this IV candidate is that there was a change in government in Argentina in December 2015.During the ENDEI 1 period (2010–12) and the first two years of the ENDEI 2 period (2014–15), the leading political party differed

[20] This is possible given that samples were constructed to be representative of the Argentinean manufacturing sectors (by industry-size). However, because 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 whether the firm belongs to the Gran Buenos Aires region (comprising Ciudad de Buenos Aires and the main adjacent districts in Buenos Aires Province) or to the rest of the country.

from the one during the last year covered by the ENDEI 2 survey. While regulations and restrictions on trade policies were prevalent during the ENDEI 1 reference period— especially when the survey was conducted (2013)—they fell off sharply during the last year covered by the ENDEI 2 survey (2016) and dropped even more when it was conducted (2017–18).

This IV strategy rests on the idea that regulations and restrictions on trade policies imposed by the government affect the perceived obstacles to innovation in a heterogenous way for firms of different sectors, regions, and sizes, which in turn may limit the resources they dedicate to innovation activities. In particular, we hypothesize that import barriers on key goods needed to carry out innovation activities are sensitive to regulations and trade policies. We would then expect that changes in trade restrictions in 2016 decreased perceived obstacles to imports of goods for innovation activities, and consequently fostered 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[21] period; we assume that firms belonging to the same group are similarly affected by these barriers. Hence, the variability in our instrument 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, given that between these two years many import restrictions were lifted. We expect a positive correlation between the perception of obstacles in the past and the change in innovation investment, given that firms that were more restricted are the ones that increased their investment in innovation activities to a greater extent once these restrictions were removed. The conditional exogeneity assumption is plausible, given that the effect of import restrictions on goods that *are key for innovation* affects productivity levels precisely through their effects on the firm's decision to conduct or increase its innovation activities, once these barriers are alleviated. A graphical explanation of the logic of this instrument is presented in figure B.1 in appendix B.

It is important to highlight that the constructed IVs are cross-sectional and are used to instrument the *difference* in innovation investment between 2014 and 2016 (we are left with only one observation per firm). As a result, the database loses its panel data structure. First differences, however, eliminate the effect of time-invariant omitted covariates.

4.3 Measurement Issues

4.3.1. Measuring the Capital Stock

To estimate equation [1], we needed to produce estimations for the firms' capital stock because data on this variable are not collected in innovation surveys. Due to serious measurement errors, ENDEI 2 does not provide information about two variables that could have been used as proxy of physical capital stock (which were provided in ENDEI 1):

1. Consumption of energy, gas, and fuel. This variable could have been used as a proxy under the argument that industrial capital stock should increase at a similar rate as the consumption of energy used to operate such equipment (Frank 1959).

[21] We assume that restrictions present during the ENDEI1 period (2010–12) can represent restrictions present in 2014, given that both the political administration and the trade regulations were the same during both periods.

2. Investment in machinery and equipment. This is a flow variable accounting for gross fixed capital formation. It can help build the capital stock through the permanent inventory method.

Having tested that energy consumption worked well as proxy of capital stocks in production function using ENDEI 1, and given the absence of alternatives in ENDEI 2, we estimate energy consumption using predictions based on variables aggregated according to firm sector and size from ENDEI 1 to be applied to ENDEI 2 (see appendix C for a description).[22]

4.3.2 Methodologies to Measure Knowledge Stock

Since Griliches' seminal study in 1967, there has been an intense academic debate about how to measure the knowledge stock using investment in innovation.[23] First, there is a problem of aggregation of knowledge, because various types of knowledge are useful to the production process. Some types are embodied in people or even in the organization and some can be acquired from external parties or by doing research in-house. The literature has normally used in-house investment in R&D as a shortcut, mostly because it is easier to measure than, for instance, organizational knowledge, and it could be argued it may be complementary to any other source of knowledge. R&D is then, at best, a representative input among others in the process of knowledge capital formation.

Second, there is some debate about what the relevant lag structure involved in estimation of current knowledge stock is: that is, it might take more than one year to complete a *research* project. When that project is completed (and if it is successful), the *development* part of the project might take even longer. Moreover, knowledge formation is a cumulative process: that is, what has been done in the past is relevant for building new knowledge in the present.

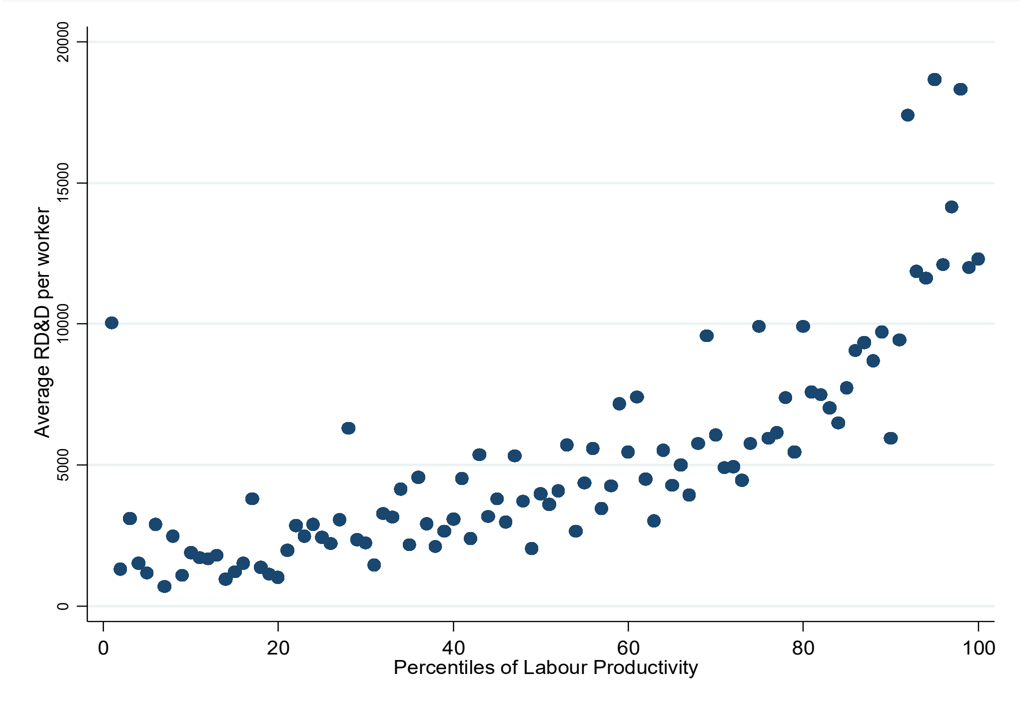
But what is the appropriate lag? The rate of depreciation may be high: Mansfield (1972) estimated an R&D lags structure, finding peaks three to five years after the investment and then declining rapidly. Little remains "private" 10 years after investment. Unfortunately, we do not have a long enough database of firms' innovation efforts to include lags in our estimation of the knowledge stock. We then need to rely on contemporaneous investment as a proxy of knowledge stock. This choice is justified by the explanation that past decisions have a great influence on both current decisions and on performance resulting from those decisions. Part of the outcome of investing in R&D is improved capacity to innovate in the future: that is, investments in R&D build the knowledge stock useful for future production. Thus, when firms decide to invest in innovation, they anticipate such efforts need to be sustained in the near future. Investment in R&D is therefore fairly sticky (Dosi 1988), and is not expected to be subject to as severe changes at the micro level as a proportion of sales or value added. Hence, what the firm invests today, relative to other firms, could be a relevant proxy of what the firm has invested in the past in relative terms.

One final key methodological element relates to the measure of all relevant types of knowledge

[22] We tested different alternatives to measure capital stock. Among them we also used the one proposed by Galiani, Gomez, and Scattolo (2019), also part of this project. All results are strongly robust. Our measure allows more variability of capital stock across sectors without information loss (no missing values are created with our procedure). Given that sectoral and regional sample representation is key to answer our research question, we prefer to use our proposed proxy of capital stock.
[23] Griliches (1967) estimated that firm's R&D and firm's productivity are connected in a bell-shaped lag structure. Since then, several strategies have been followed, typically using R&D and its lags.

besides R&D. In this paper, we also consider investment in design and industrial engineering. The reason for this is twofold. First, in several types of manufacturing (such as making wearing apparel), knowledge is incorporated mainly in the production process design. Because potential complementary factors are measured at the sectoral level, we need to be sure we incorporate the sectoral specificities of 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). Second, design and engineering implies in-house efforts that often cannot be distinguished from R&D (especially development) efforts (Cox 1990). In many firms, these types of knowledge activities are performed mainly by the same human resources and are very difficult to disentangle one from another. Indeed, all guidelines for innovation surveys globally explicitly discuss the difficulties of differentiating both types of knowledge. This is also the case for ENDEI.[24] Thus, for conceptual and methodological reasons, it is better to add design and engineering to R&D (RD&D, research design and development) in our measurements of firms' knowledge stock formation. Figure 7 presents average levels of RD&D per worker per productivity percentile, clearly showing a positive relationship, as expected with a good measure of knowledge investments.

Figure 7. Average Investment in RD&D per Worker per Each Percentile of Labor Productivity



Note: RD&D = research design and development.

[24] We cite the ENDEI questionnaire: "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 engineering; 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."

5. Results

5.1. Production Function

Table 1 shows results for the baseline estimation of equation [1]. The dependent variable is value added per worker. Production factors include labor, physical capital, and knowledge capital (proxied by energy consumption and RD&D, respectively, as previously explained) and rescaled to per worker units. All variables are expressed in natural logarithms.

In addition to the baseline model, we include alternative specifications in the table to check for (i) the effectiveness and significance of estimation methods in dealing with potential endogeneity issues, and (ii) the robustness of estimated coefficients, mainly for the knowledge stock proxy, which is the main focus of the study. We analyze the stability of coefficients' running pooled ordinary least squares (OLS) (column 1), panel (column 2), and second-difference (2014–16, column 4)[25] models using our preferred set of explanatory variables expressed as per worker ratios. We also conduct panel regressions using variables in levels instead of the per worker units (column 3); and pooled (column 5) and panel (column 6) regressions using R&D instead of RD&D as proxies of knowledge stock.

Our preferred specification corresponds to column 2, where the coefficients for labor, capital, and knowledge factors are statistically significant and show the expected signs: a 10 percent increase in RD&D per worker increases productivity by 0.09 percent, and a 10 percent increase in energy consumption per worker increases productivity by 3 percent. The coefficient for labor is significant and negative, which implies decreasing returns to scale.[26]

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 2, 3, and 4). For pooled estimations, in contrast, the coefficient is much larger (1.7 times larger than fixed effects, FE) (column 1 against column 2), which may suggest 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, in terms of better ability to manage R&D projects and production processes in general.[27]

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

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[25] For this specification, we took differences of all variables between 2014 and 2016 as in our IV estimation. Hence, this column allows us to compare results with and without instrumenting RD&D in the production function.

[26] In all estimations of table 1 except column 3, all variables are in units per worker (divided by L). Because 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 $\gamma + \delta + \theta < 1$ (that is, decreasing returns to scale).

[27] When the knowledge stock is approximated by R&D (column 6), we also find the significant and positive effect on productivity. However, when comparing results for R&D with and without FE (columns 5 and 6), the bias is negative, which means that if it is caused by omitted variables, they are correlated in opposite directions to R&D and to productivity. This may suggest that there are omitted innovative efforts that work as substitutes for R&D (but affect productivity positively). This may be the case for design and engineering, given that, as noted, it is very difficult for respondents to empirically discriminate between them.

Table 1. Results for Baseline Estimation of Equation [1]

Variables	(1) VA per worker	(2) VA per worker	(3) VA	(4) Changes VA per worker	(5) VA per worker	(6) VA per worker	(7) GMM estimates
Capital	0.32***	0.30***	0.33***	0.32***	0.32***	0.30***	0.31***
	(0.032)	(0.032)	(0.038)	(0.041)	(0.032)	(0.032)	(0.042)
RD&D	**0.015*** **	**0.0088** **	**0.0083** **	**0.0067***			0.097**
	(0.003)	**(0.0035)**	**(0.0035)**	**(0.0037)**			(0.048)
Labor	0.062**	-0.26***	0.30***	-0.027	0.068**	-0.20***	-0.014
	(0.028)	(0.045)	(0.11)	(0.048)	(0.028)	(0.048)	(0.048)
R&D					**0.017*** **	**0.074*** **	
					(0.003)	**(0.019)**	
Dummy 2015	0.17***	0.18***	0.18***		0.18***	0.18***	
	(0.014)	(0.015)	(0.016)		(0.013)	(0.015)	
Dummy 2016	0.35***	0.35***	0.33***		0.34***	0.34***	
	(0.021)	(0.023)	(0.026)		(0.021)	(0.023)	
Missing dummy [a]	0.061*	0.090*	0.080	0.048**	0.068*	0.85***	0.066**
	(0.033)	(0.048)	(0.048)	(0.024)	(0.037)	(0.23)	(0.029)
Constant	9.26***	10.6***	10.7***	0.33***	9.27***	10.4***	0.30***
	(0.29)	(0.38)	(0.40)	(0.027)	(0.28)	(0.38)	(0.028)
Observations	9,246	9,246	9,254	2,949	9,246	9,246	2,949
R-squared	0.159	0.390	0.397	0.055	0.158	0.393	
Number of ID	3,489	3,489	3,490		3,489	3,489	
Firm FE	No	Yes	Yes	No	No	Yes	No

Note: FE = fixed effects; GMM = generalized method of moments; R&D = research and development; RD&D = research design and development; VA = value added. Standard errors are clustered at the sector-size level.

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

a. We replaced missing values of investment in R&D and Industrial Design with zero in order to avoid losing observations. We control for this underestimation of our stock of knowledge variable by including a dummy that indicates whether the firm reported missing values in any of these categories or not. The estimated coefficient has the expected sign and is almost always statistically significant.

5.2.Instrumentation of Knowledge in the Production Function

Our procedure consists of using generalized method of moments (GMM) to re-estimate the equation presented in column 4 in table 1. As mentioned, we use as instruments both the dummy indicating knowledge of public support for innovation and the sector-region-size intensity of past perceived barriers to import key goods for innovation. IV results are presented in table 2. Column 1 presents the first-stage results and column 2 presents the GMM results (which repeat the specification in column 7, in table 1). First-stage results reveal the expected signs and significance for both instruments.

The test for weak instruments (Montiel-Pflueger test) (Olea and Pflueger 2013), which considers the clustered error structure of the models, gives evidence of rejecting weak instruments hypotheses.[28] In addition, because our IV model is overidentified—that is, the number of instruments exceeds the number of endogenous regressors—we can test whether instruments are uncorrelated with the error term by means of a Sargan (1958) test. In this procedure, a significant test statistic represents either an invalid instrument or an incorrectly specified structural equation. Table 2 shows that the statistic is not significant, supporting the validity of our instruments.

Table 2. Instrumental Variables Estimation

Variables	(1) First Stage	(2) GMM estimates
Prop. of firms affected by barriers to imports	0.89***	
	(0.27)	
Knowledge of financial programs	0.22**	
	(0.094)	
RD&D		0.097**
		(0.048)
Capital	0.13	0.31***
	(0.11)	(0.042)
Labor	-0.21**	-0.014
	(0.089)	(0.048)
Missing dummy	-0.27*	0.066**
	(0.15)	(0.029)
Constant	0.0049	0.30***
	(0.11)	(0.028)
Observations	2,949	2,949
R-squared	0.010	
Overidentif restric test		
Sargan statistic	1.79	
Pvalue	0.1809	
Weak IV test		
M-P Statistic	8.825	
tau=5% Critical Value	8.48	

Note: Standard errors are clustered at the sector-size level. For weak IV test, tau = % of worst case bias. RD&D = research design and development.

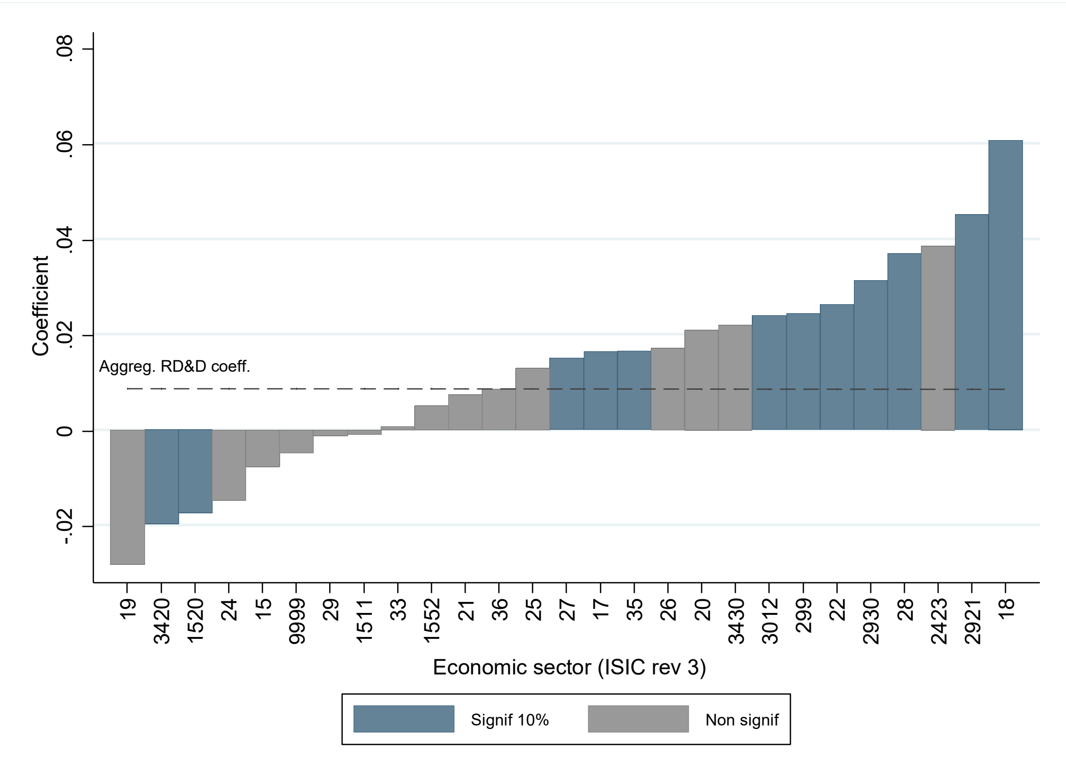
[28] The test rejects the null hypothesis that the Nagar bias of the second-stage coefficient of RD&D exceeds 5% of the "worst case bias": that is, the case in which instruments are completely uninformative and first and second stage errors are perfectly correlated.

Second-stage results show that the physical capital proxy and labor coefficients are fairly robust. The capital coefficient is close to 0.3 and labor coefficient is insignificant, as in the OLS estimation using variables in differences (table 1, column 4). The RD&D coefficient shows a positive and significant impact in labor productivity, but its magnitude is almost 15 times larger than the specification without instrumenting (table 1, column 4), which calls into question the accuracy of the instrumentation procedure.

5.3 Measuring Different Returns to Investment in Knowledge Stocks by Sector and Region

Given that the main focus of this analysis is to explain differences in RD&D returns across sectors and regions, equation [1] is estimated by sector using the specification in column 2, table 1. Coefficients for RD&D are presented in figure 8, 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 labor productivity, appear to be particularly large for wearing apparel (18), machinery for agriculture (2921), and pharmaceutical products (2423), although the latter coefficient is not significant.

Figure 8. Estimated Coefficients for Sectoral Returns to RD&D

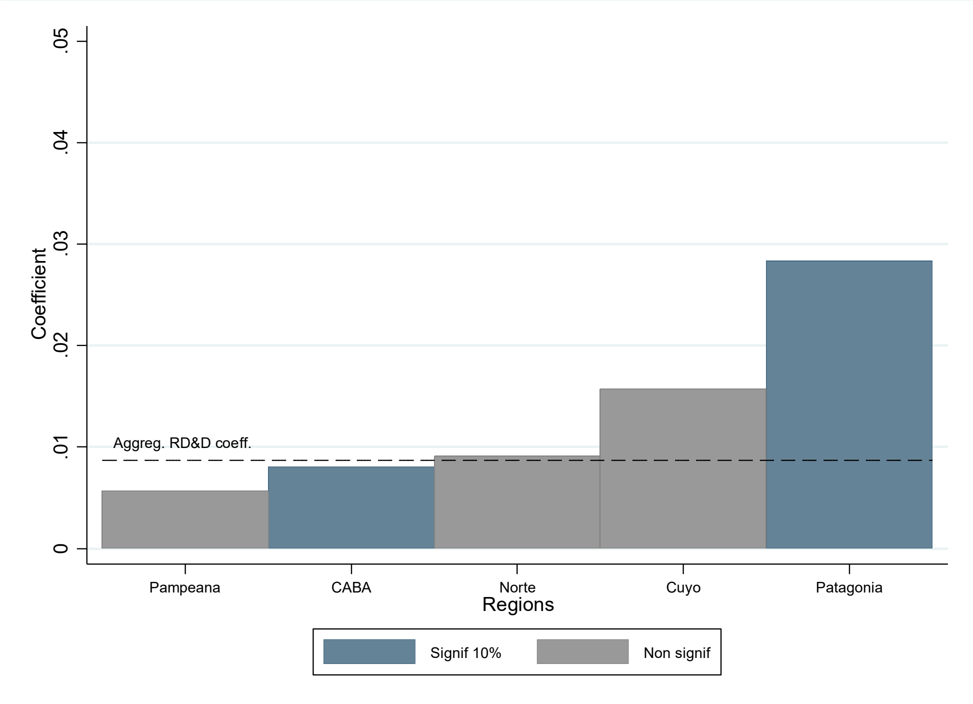


Note: For a list of economic sectors, see appendix E. ISIC = International Standard Industrial Classification; RD&D = research design and development.

[29] F test statistic for Ho: coefficients are the same across sectors, rejects at 1% level.

Figure 9 presents the returns to RD&D when calculated separately by regions. Except for returns in the Patagonia region,[30] they are less heterogeneous[31] (we suspect this may be a result of data being too aggregated at the regional level). Differences in coefficients are also statistically significant across sector/region groups.

Figure 9. Estimated Coefficients for Regional Returns to RD&D



Interestingly, the variance across sector/region groups for RD&D coefficients is much greater than the one for the coefficients for the other variables in our production function. Specifically, the coefficient of variation for RD&D coefficients across sectors is between 2.25 and 2.5 times greater than that of the coefficients for labor and capital. This seems to indicate that sectoral- and regional- specific factors have a greater effect on RD&D returns than on the other variables, leading to greater dispersion of this estimator. This raises the question of which factors are relevant to explain the larger heterogeneity in RD&D returns across sectors and regions.

This large heterogeneity across sectors and regions also appears to exist in differences in market and knowledge complementary factors. Figures B.2 and B.3 of appendix B show the variation of some these variables. For instance, inhabitants in the northern region of the country lag in economic and educational levels. Looking at sectors, the pharmaceutical products sector (2433) has larger firms or a greater supply of academic publications that are relevant to the industry. This heterogeneity in some complementary factors may explain the estimated heterogeneity in returns to RD&D.

Figure B.4 shows the relationship between certain of those market and knowledge context-based characteristics and returns to innovation per sector. Four quadrants were built divided by the median value of contextual variables and RD&D returns as shown in Figure 8. The color

[30] The Patagonia region is a special case in terms of *labor* productivity because it is specialized in capital- and natural resources–intensive industries and receives strong fiscal and economic support from the state for certain economic activities.

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

of each quadrant in the panels is given by the proportion of observations falling in that quadrant, divided by the total number of observations. Therefore, a more intense background indicates that a greater proportion of observations fall this that quadrant. These panels seem to indicate that returns to RD&D investments hold a negative relationship with sectoral financial volatility (a proxy for uncertainty), and a positive, though weaker, correlation with the proportion of migrants holding university degree in the area (a proxy for regional spillovers).

In sum, as reported by the descriptive statistics for the national context presented in section 2, this section suggests that both returns to RD&D and market and knowledge factors differ significantly across sectors and regions. In the discussion that follows, we analyze the drivers for micro-level heterogeneity, assessing the role of context-based factors in boosting or lowering returns to innovative efforts.

5.4. The Role of Context-Based Complementary Factors

The challenge when analyzing the impact of potential complementary factors is the large list of candidates that can influence the returns to knowledge investments suggested by the literature summarized in section 3. To reduce this complexity, we built several indicators to proxy the six types of contextual factors described in section 3: STI policy; spillovers (sectoral and regional); demand; competition; regulation; and uncertainty. The details on how these indexes are constructed are summarized in table A.1 (appendix A).

To avoid including too many variables in the same regression—given that this can introduce collinearities and excessive loss of degrees of freedom—we first estimate six separate regressions, one for each of the groups of contextual factors (table A.2 of appendix A), as a way to explore them one at a time. From each regression, we chose the variable(s) that had a significant effect on productivity, with or without interacting with RD&D.[32] We proceeded to include this subset of selected variables in single specifications, presented in table A.3. The table has eight columns because we had more than one candidate within some groups of contextual factors, which led us to a set of possible specifications. Among these options, our chosen estimation is the one presented in column 8. Appendix A explains why we consider this the best combination of contextual variables available.

Column 8 of table A.3 presents several interesting results. First, both **intra-sector spillovers** (expenditure on *innovation per sector/region*) and **demand** factors (*sector-region exports*) seem to be positively correlated with productivity levels (a double interaction), although not through RD&D investments (a triple interaction). The same holds for **competition**, measured by the Herfindahl index: a negative coefficient indicates that more concentrated markets are less productive on average, although the channel driving this relationship does not seem to be RD&D returns. Hence, these results suggest the existence of other unidentified channels that explain the relationship between these contextual factors and productivity. Examples of alternative channels could be that firms design other strategies apart from RD&D investments to absorb innovation spillovers or that higher levels of competition can lead managers to invest more in worker skills and human capital formation, which we are not measuring in our estimation.

[32] We did not produce IV estimates in this case because the IV procedure renders coefficients that are too large relative to FE in our knowledge production function estimation (table 1, column 7 versus column 4). In addition, it does not seem very feasible to find suitable instruments for all the necessary interactions. As a result, we focus primarily on describing the sign of the impact on the returns rather than the size effect, given the likely bias in the estimates.

In addition, **inter-sectoral spillovers** (*university migrants*) and our variable measuring market **uncertainty** are related to productivity through *RD&D returns*. For the former, a positive coefficient for the triple 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 result is not surprising and could be led by the fact that a higher supply of educated workers increases RD&D returns, or more productive and innovative areas attract people with higher educational levels. Results for financial volatility are also as expected: sectors that suffer from more financial uncertainty have lower returns on innovation.

A puzzling result arises when **STI policy** (proxied by *Publications*) is interacted with RD&D. One potential explanation for this negative coefficient could be the existence of a substitution effect between firms doing in-house innovation versus those relying on external (public) knowledge embedded in publications relevant for their sector.

Finally, we find no significant relationship between productivity and **regulatory** measures. This can be the result of a lack of appropriate measurement, given that a vast literature suggests that the regulatory environment affects innovation incentives and results.

5.5. The Effect of Context-Based Factors via Innovative Capacity

The fact that in some cases contextual factors affect productivity directly, rather than through RD&D, suggests that innovative capacity or ability embedded in firm-level management processes and decisions may mediate the effect of contextual factors, mitigating or augmenting them.

We proxy this innovative capacity or ability using questions about managerial attitudes and skills in sections 2 and 7 from ENDEI 2. Specifically, we build indicators of managerial attitudes and skills that may account for firms' innovative capacity to benefit from *each* contextual factor. So, for example, an indicator that specifies which external sources of information the firm uses for innovation is relevant for the firm to be able to benefit, or not, from STI policies or spillovers. Similarly, firms that are technological leaders are more likely to be positively affected by contextual competition because greater competition will push them to increase their innovation activity to maintain their leadership.

To explore the role of these firm-level factors, the coefficients of interest are those that correspond to the *triple interaction* of RD&D, the context-based complementary factor, and the firm-level proxies of innovative capacity (in dealing with complementary factors). The level and significance of these estimators allows us to assess whether certain types of firms' attitudes make them better prepared to benefit from or to be held back by their context.

Table D.1 in appendix D describes each indicator built to account for firms' strategies (that is, innovative capacity) to benefit from each context-based complementary factor. In order to decide which of those managerial skills were actually relevant, we follow a procedure similar to the one used to select the contextual variables already described. First, we estimate separate regressions (table D.2). Then we select the significant ones for a second step where we include all of them together (table D.3). Results in table D.3 expand the set of conclusions derived from table A.3.

The results show that **STI policy** is now positively related to productivity for firms that rely on external sources of information. A feasible interpretation of this result is that firms are positively affected by being in an environment with higher supply of scientific articles if they have a strategy of pursuing learning from external sources. However, the coefficient multiplying the triple interaction of **STI policy**, RD&D, and our firm-specific dummy is negative and significant. This reinforces the potential existence of a substitution effect highlighted earlier. A greater external supply of information relevant for innovation may lead firms to rely less on internal RD&D procedures. Therefore, scientific knowledge has a positive effect on productivity for firms that use it (a positive double interaction), but is particularly important for firms that do not rely on internal efforts such as RD&D investments (a negative triple interaction).

Also, firms' attitudes toward external sources of information interact positively with intra-sectoral **spillovers**, while the triple interaction remains insignificant. A likely interpretation for this result is that firms open to external sources of information benefit from intra-sectoral spillovers, regardless of whether they invest or not in RD&D.

Results regarding **demand** contextual factors show a positive relationship with productivity for all types of firms, although the channels driving this relationship differ. On the one hand, firms that declare demand to be a main driver for investment in innovation (variable DEM=1) seem to take better advantage of demand variables for their RD&D investments, consequently raising productivity (a positive triple interaction). On the other, for those firms that are not specifically motivated by demand for innovation, unspecified channels cause demand and firm productivity to positively correlate (a positive double interaction, DEM=0 * Exports).

Including interactions to account for firm' strategies also reveals new results for market **competition** factors. Firms that act in the market as technological leaders increase their returns to RD&D when the market is more competitive (the triple interaction is negative for Herfindahl*RD&D*Technoleader). This result is consistent with the predictions from Schumpterian theory (Aghion and Jaravel 2015). Competition also proves to be beneficial for the productivity of firms that are not technological leaders, as well, but through channels other than RD&D returns (a double interaction, Herfindahl*non-technological leader is negative). In fact, competition seems to harm the returns to RD&D for non-leaders.

While limited by our inability to measure some of these management strategies, the results suggest that innovative capacity, largely due to the quality of managerial practices, is likely to explain a portion of the observed heterogeneity in the returns to innovation, by means of enabling firms to take better advantage of context-based factors.

6. Conclusions and Implications for Policy

Main Findings

This paper presents new evidence to try to understand which factors are affecting the returns to innovation in Argentina, which can help address the dismally low volume of private R&D investment. The results show that returns are quite heterogeneous, which is likely to translate into the fairly low level of in-house private efforts to spur innovation and productivity growth. Our results suggest that different context-based factors, at the regional and sectoral levels, affect these returns. The findings also show that such effects are not homogeneous across firms but depend on firms' strategies— referred to here as innovation capacity—which vary across firms.

Figure 10 summarizes which context-based complementary factors appear to have an impact on innovation returns (as shown in table A.3, column 8, and table D.3), . Results fall into three groups, according to the way they relate to firm productivity.

The first group consists of results associated with our first hypothesis (H1): those context-based complementary factors holding a relationship with RD&D returns on productivity for *all firms on average*. A second set of results are those associated with our second hypothesis (H2): those context-based complementary factors holding a relationship with productivity through the RD&D channel, but *only for firms with specific innovative capacity* (that is, proactive attitudes to make the most of context-based complementary factors). In addition, a third group of results, not addressed by these two hypotheses, includes some context-based factors relating to productivity, although not through RD&D investments.

The first group refers to H1: context-based factors that are significantly correlated with the returns to RD&D whatever the strategic action/attitude toward the context the firm has. We find that **H1** is not rejected for **uncertainty**, which affects returns negatively, and **inter-sectoral spillovers,** which correlates positively. Results for both factors are as expected: more volatile contexts do not favor returns to innovation investments, while inter-sectoral spillovers enhance returns to RD&D. These are robust findings given that both variables are also statistically significant (p-value < 1% for uncertainty, p-value < 5% for spillovers) in all specifications. Hence, these two contextual factors should be particularly addressed by policies looking to boost innovation returns because, on average, they seem to have an effect on all firms.

The second group relates to **H2:** context-based complementary factors that have a significant relationship with productivity through RD&D returns, but only when mediated by some proactive attitudes by firms. We find some empirically validity for competition and demand. In the case of market **competition**, we find that it affects innovation returns positively only when mediated by the strategic position of the firm in the market (whether it is a technological leader or not). This result is important for policy because it seems to indicate that high levels of competition favor innovation of technological leaders, as has been found by the Schumpeterian literature. Policies need to consider this heterogeneous impact of competition because competition lowers the returns to RD&D investment for firms that are not leaders in their markets. A similar result appears for the **demand** factor, which is significantly related to RD&D returns only when mediated by firms' attitudes toward demand: greater demand orientation in their strategies can lead to greater investment in innovation. An unexpected result is the negative effect of **STI policy**, proxied by industry-relevant publications, on RD&D returns for firms that are particularly active in searching academic sources of external knowledge.

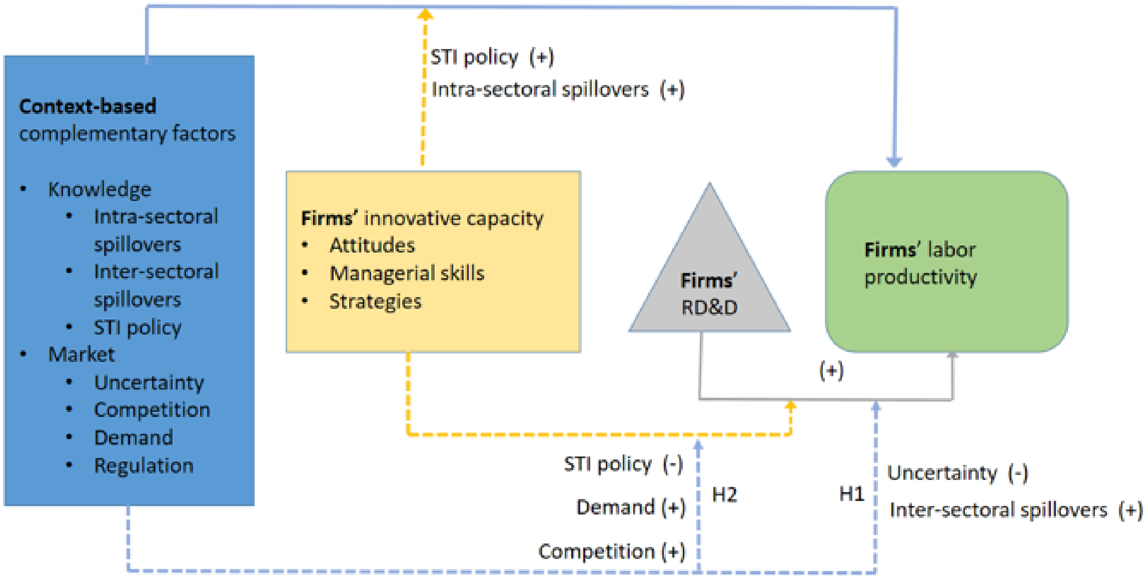
The third group includes context-based factors that affect productivity, but not through RD&D returns**. Intra-sectoral spillovers** belong to this group. When mediated by how open the firm is toward the context (that is, how many market-related external sources of information the firm uses), this factor affects productivity through other unspecified channels.

In addition, the **STI policy** factor yields interesting conclusions. Firms that consult sources from academic organizations increase their productivity when publications relevant for their industrial activity are abundant (the STI system is favorable in this regard). However, as noted, the effect through the RD&D channel is negative. This suggests a substitution effect, by which firms either rely on in-house RD&D or are nurtured by the STI environment.

Finally, we do not have enough evidence to establish a relevant relationship between **regulation** factors and productivity, either through RD&D or through any other channel. This could be due to problems in measuring these regulatory factors.

A caveat is in order in drawing conclusions from these results. Robust assessment of the causal relationship between context-based complementary factors, RD&D, and productivity is difficult to achieve with the data available. The results shown are fairly stable and we are confident that panel data estimations have minimized endogeneity issues greatly. However, instrumental variables or other quasi-experimental methods would be necessary to ensure causal interpretations of the coefficients. This could be an interesting avenue for future research with better data sets. Appendix F presents the implications from this research related to data collection and offers suggestions for improvements.

Figure 10. Synthesis of Results



Implications for Policy

The findings on the relationship between context-based and complementary factors, firm-specific strategies, and returns to investments in innovation have important implications for public policy. First, there is a need for policy to address some of the contextual factors discussed. For instance, political programs looking to provide incentives for innovation should focus on supporting firms' R&D investment in periods of economic uncertainty or promoting mobility of academics and experts across the country to favor intersectoral spillovers. This contrasts with the current view of encouraging R&D efforts via the use of tax incentives. Such incentives are procyclical by design, given that they depend on the provisions to accumulate tax credits, which can amplify the effect of uncertainty. The heterogeneous impact of competition is also relevant. Policy measures that encourage innovation in laggards could be useful in the presence of significant market failures.

The second important implication for policy is related to the relevance of regional innovation strategies. The impact of these contextual factors as complementarities to R&D and the fact that many of these factors are regional in nature suggest the importance of having flexible STI policies that adapt to the needs of the local innovation system. This recommendation is supported by the concept of "smart specialization" (Foray, David, and Hall 2011). This strategy has gained increasing popularity in Europe recently. It consists of a territorial-based setting of priorities that involves different stakeholders from academia, business organizations, policy authorities, and civil society. This is done through a process called "entrepreneurial discovery," which consists of identifying investment priorities largely grounded on local assets and resources ((Gomez Prieto, Demblans, and Palazuelos Martinez 2019). Strategies that are developed from the center with little adaptation will likely fail in addressing critical failures and the impact of contextual factors. This more decentralized approach will require "federalization" of public innovation programs and adaptability. This could be achieved by transferring the design and implementation of certain innovation policies to provincial ministries—those with greater government capabilities—and improving communication between local firms; research organizations that have regional headquarters such as CONICET (the National Scientific and Technical Research Council), INTA (the National Agricultural Technology Institute), and INTI (the National Industrial Technology Institute); regional universities; and civil society organizations.

The third critical policy implication is the need to invest in innovation capacity. Having better quality management strategies is more likely to maximize the impact of these context-based factors on the returns to R&D. For example, building these management capabilities to maximize external knowledge, or to appropriate the rewards of innovation in specific contexts, or to use and recruit talent, can be critical to maximize the impact of innovation policies. Instruments that support this building of managerial capabilities have a central role to play in innovation policy to build more sophisticated innovation policy support and should be mainstreamed in STI policies.

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Appendix A. Choosing among Contextual Variables

Table A.1. Explanation of Contextual Variables

<table>
<tr><th>Contextual factor</th><th>Variable</th><th>Variable name in tables</th><th>Explanation</th><th>Intends to measure</th><th>Period of data availability</th><th>Data source</th></tr>
<tr><td rowspan="5">Science, technology, and innovation (STI) policy</td><td>Academic publications per sector</td><td>Publications</td><td>Built from Scopus microdata on academic publications. Scopus assigns each publication a field of study. To convert this to sectoral-level data, we use a matrix built from ENIT(National Survey on Innovation and Technology Behavior) data, which offers information on how much each sector of economic activity values each field of study.</td><td>Supply of scientific knowledge per sector</td><td>2013–17</td><td>Scopus + ENIT</td></tr>
<tr><td>Proportion of people with university degree per province (EPH)</td><td>PropUniv</td><td>Proportion of inhabitants holding a university degree per province.</td><td>Supply of qualified workforce per province</td><td>2003–18</td><td>EPH</td></tr>
<tr><td>University graduates per sector</td><td>GraduatesSec</td><td>Built from micro-level data on university graduates. To convert career data to sectoral-level information, we first group careers into fields of study. We then use the same matrix as with the Scopus data to convert this to sectoral-level data.</td><td>Supply of qualified workforce per sector</td><td>2010–17</td><td>Department of universitary information</td></tr>
<tr><td>Provincial budget for higher education</td><td>HigherEduc</td><td>Public expenditure on university- and tertiary-level education as a proportion of total public expenditure by province.</td><td>Government support for building qualified workforce</td><td>2001–16</td><td>Ministry of Education</td></tr>
<tr><td>PCA (principal component analysis) of provincial budgets</td><td>PCAbudget</td><td>1st component resulting from principal component analysis (PCA). Variables included are budget amounts designated for different areas considered relevant for innovation: education and culture; primary, secondary and tertiary education; and private spending on education.</td><td>Government support for R&D activities</td><td>2001–16</td><td>National Directorate of Provincial Affairs, Sub-Secretariat of Provincial Coordination</td></tr>
<tr><td rowspan="2">Spillovers–sectoral</td><td>Innovation per sector-region</td><td>Inno_sector_region</td><td>Results from adding up investment in any innovation activity for firms within same sector and region.</td><td>Intrasectoral spillovers</td><td>2014–16</td><td>ENDEI</td></tr>
<tr><td>Intersectoral spillovers</td><td>Inno_spillover</td><td>Weighted sum of the investment in innovation in other sectors. The weights for this sum represent the importance of various sectors for a specific sector. To calculate these weights, we construct a matrix with the movement of employees between sectors across time in Argentina using EPH data. Therefore, sector A will be more relevant for another sector B if the latter has many employees who worked in sector</td><td>Spillovers of investment in innovation coming from other sectors.</td><td>2014–16</td><td>ENDEI+EPH</td></tr>
</table>

			A in the past (and are bringing their knowledge and experience to sector B).			
Spillovers–regional (spatial)	Proportion of inmigrants with university degree	MigUniv	Proportion of inhabitants of a province that are immigrants (originally from another country or province) and hold a university degree (interprovince spillovers).	Movement of qualified workforce (inter-sectoral spillovers)	2003–18	EPH
Demand	Exports sector-province	Exports	Value of yearly exports in dollars by province and sector. Prices adjusted with sectoral level price index.	Level of international demand	1997–2017	OPEX; Fares, Zack, and Martínez (2017) for price adjustments
	Unemployment rate	UnempRate	Unemployed population/Economically active population per province.	Level of demand in province	2003–18	EPH
	Mean wages	MeanSal	Mean income from main occupation per province.	Level of demand in province	2003–18	EPH
	Mean household income per capita	HHinc	Mean household income per capita by province.	Level of demand in province	2003–18	EPH
Competition	Herfindahl index (sector-region)	Herfindahl	Sector-Region Herfindahl index constructed with firm level sales data from ENDEI.	Level of competition in sector-region	2014–16	ENDEI
	Number of firms (province-sector)	NumFirms	Number of operating firms in province-sector.	Level of competition in sector-province (when this proxy is used, we control by sector-province size using total employment)	1996–16	OEDE
	Average firm size (province-sector)	FirmSize	Total employment/Number of firms at province-sector level.	Level of competition in sector-province	1996–16	OEDE
	Employment sector-province	Employment sector-province	Total number of employees per sector-province.	Control for market size when including number of firms as competition variable	1996–2018	OEDE
Regulation	Proportion of people in informal sector	PropInformal_SEC	Proportion of employees in each sector stating they are not contributing to a formal pension system.	Intends to measure regulation in sector. Higher informality is a sign of less regulation	2003–18	EPH
	Google searches on corruption topics (province)	Corruption_GT	Google trends index on searches of words related to corruption by province. This index is constructed in a way to control for the total amount of google searches per province and period of time.	Level of corruption per province. Assumes that inhabitants of provinces with more corruption tend to search more on corruption related topics	2004–19	Google Trends

	Opening + Closing of firms	FirmEntryExit	(# Firm Entry+ # Firm exit)/ # of Firms per province.	Represents dynamism of industry in each province. A higher value of this variable means that there are less regulations for opening and closing a business	1996–2016	OEDE
	Proportion of people affiliated to a political party	PropAffil	Proportion of voting population affiliated to a political party per province	Measure of accountability for each province. Higher levels of affiliation represent a greater control of the state by the population, which tends to lead to better economic institutions.	2013–17	National electoral chamber
	Wage deviation by sector (EPH)	WageDev	Coefficient of variation of individual level data on wages per sector	Attempts to measure power of trade unions in each sector, as these tend to decrease the dispersion of salaries.	2003–18	EPH
Uncertainty	Volatility of financial credits (per sector)	Volat_credit_sect	Std deviation of residuals of AR(1) model using data on financial credits at sectoral level	Market uncertainty. A higher variance in the residuals of an autoregressive process indicates that the variable is less predictable.	2000–17	BCRA
	Volatility of financial credits (per province)	Volat_credit_prov	Std deviation of residuals of AR(1) model using data on financial credits at province level		2000–17	BCRA
	Volatility of imports	Volat_imports	Std deviation of residuals of AR(1) model using data on sectoral imports		1962–2018	COMTRADE
	Volatility of interest rate	Volat_intrate	Std deviation of residuals of AR(1) model using data on sectoral level nominal interest rates		2000–17	BCRA
	Volatility of export price	Volat_priceX	Std deviation of residuals of AR(1) model of sectoral level export prices		1996–2016	Fares, Zack, and Martínez (2017)
	Volatility of exports (per province)	Volat_expo_prov	Std deviation of residuals of AR(1) model using data on exports at province level		1997–2017	OPEX
	Volatility of exports (per sector)	Volat_expo_sect	Std deviation of residuals of AR(1) model using data on exports at sectoral level		1997–2017	OPEX
	Volatility of exchange rate (per sector)	Volat_ER	Std deviation of residuals of AR(1) model using data on exchange rate at sectoral level		2010–18	Secretariat of Productive Transformation

Note: BCRA = Central Bank of Argentina ; COMTRADE = United Nations International Statistics database; ENDEI = Employment and Innovation Dynamics National Survey; ENIT = National Survey on Innovation and Technology Behavior, EPH = Permanent Household Survey ; OEDE = Observatory of Labor and Firm Dynamics; OPEX = Provincial origin of Argentine Exports

In table A.2, each column presents estimations for the production function, including all indicators built to account for each context-based factor, using the specification in column 2 from table 1 in the main text. Indicators that are statistically significant are boldfaced.

Based on significant variables from table A.2, we then estimated many alternative regressions taking into account variables that were highly correlated, and situations when more than one variable was significant within the same group (recall that our interest lies in getting a good proxy variable for the contextual factor that it represents). Results can be seen in table A.3.

Column 1 includes one significant variable from each context-based factor, excluding regulation because there was not any relevant result in that case. Column 2 includes the proxy for regulation that we are more confident about (entry plus exit of firms, which suggests bureaucratic ease to promote business dynamism).

Since coefficients do not change much, for the sake of completeness we decided in favor of column 2 (including regulation). In column 3, we changed our proxy for STI policy, using university graduates per sector instead of academic publication per sector. Akaike information criterion (AIC), Bayesian information criterion (BIC), and the significance of coefficients drive us to choose column 2.

Column 4 changes the proxy for spillovers; instead of using the proportion of university immigrants in the region, which accounts for inter-sectoral spillovers, we include the average innovation expenditures per sector region, which accounts for intra-sector spillovers. Although the variable for intra-sectoral spillover is significant, results are marginally better for the former, in terms of AIC and BIC criterion, so we stick to results in column 2.

In column 5 we change the proxy for competition; instead of using the number of firms in the sector-province, we use the Herfindahl index. Results improve, according to AIC and BIC criterion, leading us to choose in favor of the specification in column 5.

Columns 6 and 7 change our proxy for uncertainty, using volatility of exports and imports, respectively, instead of volatility of credit resources. Results do not improve, so we stick to column 5.

Finally, in column 8, we include both variables for spillovers (inter-sectoral and intra-sectoral) that we have tested for separately, and results improve. Since they conceptually account for different aspects of spillovers, both remain significant. AIC criteria suggest this is the best specification, so we opt for that one to continue the analysis.

Table A.2. Results for Equation [2], Including Several Proxies of Complementary Factors
Each column presents one specification for each of the six complementary factors identified in figure 5

VARIABLES	(1) STI policy	(2) Spillovers	(3) Demand	(4) Competition	(5) Regulation	(6) Uncertainty
Capital per worker	0.30***	0.30***	0.30***	0.30***	0.30***	0.30***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
R&D+D per worker	-0.0036	-0.0010	0.0065	0.0042	0.00010	0.0077
	(0.020)	(0.0054)	(0.011)	(0.0049)	(0.012)	(0.0047)
Labor	-0.26***	-0.26***	-0.26***	-0.25***	-0.26***	-0.26***
	(0.046)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Year 2015 dummy	0.20***	0.18***	0.18***	0.18***	0.18***	0.17***
	(0.018)	(0.017)	(0.019)	(0.015)	(0.017)	(0.018)
Year 2016 dummy	0.35***	0.34***	0.32***	0.35***	0.34***	0.33***
	(0.031)	(0.031)	(0.050)	(0.023)	(0.024)	(0.028)
Missing dummy	0.10**	0.085*	0.091*	0.099**	0.095**	0.098**
	(0.049)	(0.046)	(0.048)	(0.048)	(0.047)	(0.047)
Academic publications per sector	**19.6****					
	(8.16)					
Prop of people with university degree per prov	-1.37					
	(1.41)					
University graduates per sector	-1.38					
	(4.49)					
Provincial Budget for higher education	0.26					
	(0.34)					
PCA of provincial budgets	-0.025					
	(0.022)					
RD&D p.w. * Publications	-0.14					
	(0.24)					
RD&D p.w. * PropUniv	0.21					
	(0.15)					
RD&D p.w. * GraduatesSec	-0.23					
	(0.21)					
RD&D p.w. * HigherEduc	-0.0018					
	(0.049)					
RD&D p.w. * PCA Budget	0.00085					
	(0.0028)					
Innovation per sector-region		**3.04****				
		(1.18)				
Intersectoral spillovers		-0.37				
		(1.08)				
Prop of inmigrants with univer degree		1.93				
		(2.89)				
RD&D p.w. * Inno_sector_region		-0.14				
		(0.11)				
RD&D p.w. * Inno_spillover		0.088				
		(0.087)				
RD&D p.w. * MigUniv		**0.36****				
		(0.15)				
Exports sector-province			**0.016*****			
			(0.0055)			
Unemployment rate			1.10			
			(1.09)			
Mean salary			1.33			
			(7.15)			
Mean household income per capita			0.048			
			(6.18)			
RD&D p.w. * Exports			0.00017			
			(0.00046)			
RD&D p.w. * UnempRate			0.041			
			(0.14)			
RD&D p.w. * MeanSalar			0.39			
			(0.35)			
RD&D p.w. * HHincome			-0.43			
			(0.39)			
Herfindahl index				**-0.00010****		
				(0.000040)		
Number of firms				-7.82		
				(24.9)		
Average firm size				-4.0e-09		

				(1.1e-08)		
RD&D p.w. * Herfindahl				1.7e-06		
				(2.0e-06)		
RD&D p.w. * NumFirm				**0.41***		
				(0.22)		
RD&D p.w. * Firm size				-1.9e-10		
				(5.7e-10)		
Employment sector-province				-4.8e-06		
				(9.8e-06)		
Proportion of people in informal sector					0.061	
					(0.079)	
Google searched on corruption topics					0.00083	
					(0.00055)	
Entry+ Exit of firms					0.37	
					(0.62)	
Prop of people affiliated to a political party					0.056	
					(0.039)	
Wage deviation by sector (EPH)					-0.042*	
					(0.025)	
RD&D p.w. * PropInformal_SEC					0.0060	
					(0.0097)	
RD&D p.w. * Corruption_GT					8.2e-06	
					(0.000054)	
RD&D p.w. * FirmEntryExit					0.090	
					(0.072)	
RD&D p.w. * PropAffil					-0.0040	
					(0.0040)	
RD&D p.w. * WageDev					-0.0060	
					(0.0040)	
Volatility of financial credits (sector)						97.7
						(105)
Volatility of imports (sector)						-616
						(433)
Volatility of interest rate (sector)						58.1
						(73.8)
Volatility of export price (sector)						**-190*** **
						(54.5)
Volatility of financial credits (province)						-47.0
						(64.8)
Volatility of exports (province)						-103
						(67.7)
Volatility of exports (sector)						123
						(77.4)
Volatility of exchange rate (sector)						-0.0062
						(0.0069)
RD&D p.w. * Volatility of imports (sector)						-17.6
						(13.7)
RD&D p.w. * Volatility of interest rate (sector)						10.7
						(7.73)
RD&D p.w. * Volatility of financial credits (province)						**-35.1*** **
						(12.2)
RD&D p.w. * Volatility of export price (sector)						1.37
						(11.7)
RD&D p.w. * Volatility of financial credits (province)						3.52
						(10.5)
RD&D p.w. * Volatility of exports (province)						5.68
						(9.50)
RD&D p.w. * Volatility of exports (sector)						-2.05
						(11.8)
RD&D p.w. * Volatility of exchange rate (sector)						0.00061
						(0.00084)
Constant	10.5***	10.6***	10.5***	10.9***	10.6***	10.7***
	(0.45)	(0.39)	(0.38)	(0.47)	(0.39)	(0.38)
Observations	9,246	9,246	9,246	9,176	9,246	9,246
R-squared	0.391	0.391	0.391	0.390	0.391	0.393
Number of ID	3,489	3,489	3,489	3,471	3,489	3,489

Note: Indicators that are statistically significant are boldfaced. EPH = Permanent Household Survey**;** PCA = principal component analysis; p.w. = per worker**;** R&D +D = research design and development; STI = science, technology, and innovation. Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3. Results for Equation [2], Including Simultaneously One Indicator for Each Complementary Factor Identified in Figure 5[a]

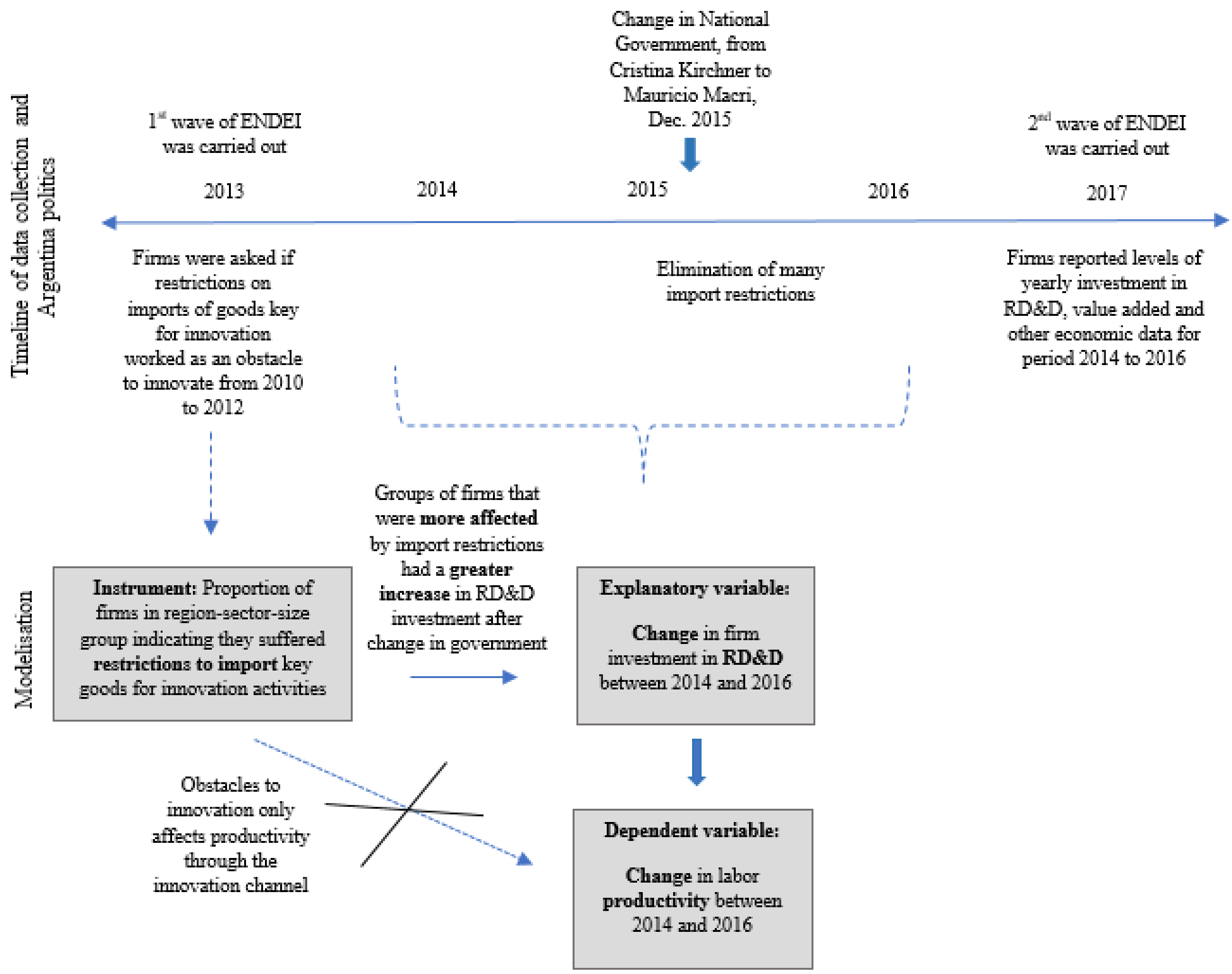
Contextual Factor	VARIABLES	(1) No regulation	(2) Including Regulation	(3) Change STI policy	(4) Change Spillovers	(5) Change competition	(6) Change Uncert	(7) Change Uncert	(8) Both Spillovers
	Capital per worker	0.30***	0.30***	0.30***	0.30***	0.30***	0.30***	0.30***	0.30***
		(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
	R&D+D per worker	0.0022	-0.0075	-0.0039	0.0022	-0.0040	-0.0044	-0.0043	-0.0030
		(0.0060)	(0.012)	(0.013)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)
	Labor	-0.26***	-0.26***	-0.26***	-0.26***	-0.26***	-0.26***	-0.26***	-0.26***
		(0.045)	(0.045)	(0.045)	(0.045)	(0.046)	(0.046)	(0.045)	(0.046)
	Year =2015	0.20***	0.20***	0.19***	0.19***	0.19***	0.18***	0.19***	0.19***
		(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)
	Year =2016	0.32***	0.31***	0.35***	0.32***	0.33***	0.33***	0.33***	0.32***
		(0.027)	(0.028)	(0.026)	(0.027)	(0.028)	(0.029)	(0.028)	(0.029)
	Missing dummy	0.099**	0.100**	0.100**	0.10**	0.098**	0.098**	0.096**	0.100**
		(0.049)	(0.048)	(0.048)	(0.050)	(0.047)	(0.048)	(0.047)	(0.047)
STI policy	Acad. publications per sector	21.1**	21.2***	-	15.0*	15.9**	13.4*	13.2	8.81
		(8.07)	(8.03)	-	(8.99)	(7.49)	(7.86)	(8.02)	(8.50)
STI policy	University graduates per sector	-	-	-1.69		-	-	-	-
		-	-	(4.11)		-	-	-	-
Spillovers	Prop of inmig with univer degree	1.91	2.64	2.76	-	2.64	2.65	2.62	2.78
		(2.90)	(3.24)	(3.25)	-	(3.19)	(3.18)	(3.20)	(3.19)
Spillovers	Innovation per sector-region	-	-	-	2.83**	-	-	-	3.08***
		-	-	-	(1.25)	-	-	-	(1.14)
Demand	Exports	0.017***	0.017***	0.017***	0.020***	0.017***	0.016***	0.016***	0.020***
		(0.0057)	(0.0057)	(0.0055)	(0.0060)	(0.0058)	(0.0057)	(0.0057)	(0.0062)
Competition	Number of firms	-28.9	-28.4	-9.36	-31.3	-	-	-	-
		(26.0)	(25.9)	(26.0)	(26.0)	-	-	-	-
Competition	Herfindahl (sector-region)	-	-	-	-	-0.96**	-0.89**	-0.97**	-1.01***
		-	-	-	-	(0.38)	(0.38)	(0.38)	(0.38)
Regulation	Firm Entry+Exit	-	0.58	0.56	0.37	0.72	0.70	0.69	0.67
		-	(0.70)	(0.70)	(0.62)	(0.71)	(0.71)	(0.71)	(0.70)
Uncertainty	Volatility of financial credits	110	111	116	115	86.6	-	-	89.6
		(101)	(101)	(102)	(100)	(102)	-	-	(101)
Uncertainty	Volatility export prices	-	-	-	-	-	-162***	-	-
		-	-	-	-	-	(53.3)	-	-
Uncertainty	Volatility imports	-	-	-	-	-	-	-602	-
		-	-	-	-	-	-	(433)	-
STI policy	RD&D p.w * .Publications	-0.30	-0.34*	-	-0.30	-0.36*	-0.38**	-0.37	-0.38*
		(0.20)	(0.20)	-	(0.23)	(0.20)	(0.19)	(0.23)	(0.23)
STI policy	RD&D p.w. * Univgraduates	-	-	-0.17	-	-	-	-	-
		-	-	(0.15)	-	-	-	-	-
Spillovers	RD&D p.w * MigUniv	0.40**	0.39**	0.37**	-	0.39**	0.41**	0.41**	0.40**
		(0.16)	(0.15)	(0.15)	-	(0.18)	(0.18)	(0.18)	(0.18)
Spillovers	RD&D p.w. * Inno sector-region	-	-	-	-0.020	-	-	-	-0.0067
		-	-	-	(0.094)	-	-	-	(0.089)
Demand	RD&D p.w.* Expo	0.00018	0.00017	0.00015	0.000029	0.00013	0.00027	0.00027	0.000079
		(0.00047)	(0.00048)	(0.00049)	(0.00047)	(0.00045)	(0.00048)	(0.00050)	(0.00044)
Competition	RD&D p.w *NumberFirms	0.36*	0.38*	0.39*	0.26	-	-	-	-
		(0.20)	(0.20)	(0.20)	(0.21)	-	-	-	-
Competition	RD&D p.w * Herfindahl	-	-	-	-	0.0062	0.0064	0.0069	0.0072
		-	-	-	-	(0.017)	(0.017)	(0.018)	(0.017)
Regulation	RD&D p.w. * Firm Entry+Exit	-	0.076	0.069	0.075	0.060	0.062	0.059	0.055
		-	(0.070)	(0.070)	(0.070)	(0.071)	(0.071)	(0.072)	(0.069)
Uncertainty	RD&D p.w.*Volat finan. credit	-31.0***	-31.0***	-29.2**	-31.6***	-31.9***	-	-	-31.6***
		(11.6)	(11.6)	(11.9)	(11.4)	(11.5)	-	-	(11.3)
Uncertainty	RD&D p.w. * Volat expo prices	-	-	-	-	-	6.05	-	-
		-	-	-	-	-	(10.5)	-	-
Uncertainty	RD&D p.w. * Volat impo	-	-	-	-	-	-	-8.06	-
		-	-	-	-	-	-	(18.6)	-
	Employment (sector-province)	-7.3e-06	-6.5e-06	-4.5e-06	-6.0e-06	-	-	-	-
		(9.7e-06)	(9.8e-06)	(9.3e-06)	(9.9e-06)	-	-	-	-
	Constant	10.5***	10.4***	10.7***	10.6***	10.4***	10.4***	10.4***	10.5***
		(0.49)	(0.53)	(0.51)	(0.50)	(0.46)	(0.46)	(0.46)	(0.47)

Observations	9,246	9,246	9,246	9,246	9,246	9,246	9,246	9,246
R-squared	0.393	0.393	0.393	0.393	0.394	0.394	0.393	0.395
Number of ID	3,489	3,489	3,489	3,489	3,489	3,489	3,489	3,489
AIC	1977.5	1977.8	1988	1979.4	1963.4	1969.1	1973.8	1957.5
BIC	2098.7	2113.3	2123.5	2115	2091.8	2097.4	2102.2	2100.1

Note: Each specification alternate proxies for complementary factors; columns headings show on what factor such change occurred. p.w. = per worker; R&D +D = research design and development; STI = science, technology, and innovation. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix B. Supporting Figures

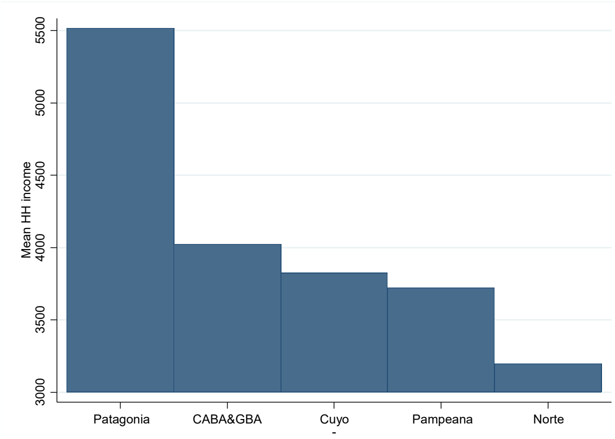
Figure B.1. Graphical representation of the 2nd Instrumental Variable (Change in Government Regulation)



Note: ENDEI = Employment and Innovation Dynamics National Survey; RD&D = research design and development.

Figure B.2. Variation of Contextual Factors among Regions

a. Average household income



b. Proportion of people with a university degree

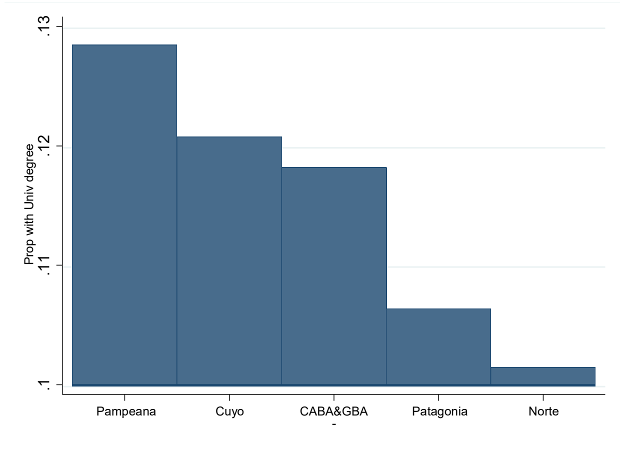
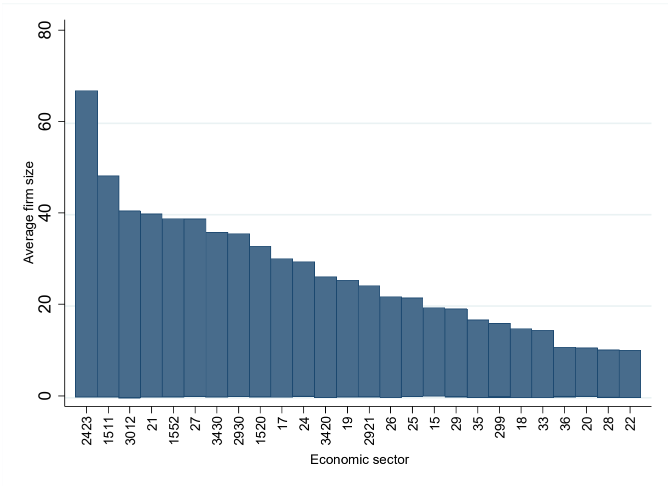


Figure B.3. Variation of Contextual Factors among Sectors

a. Average firm size



b. Academic publications

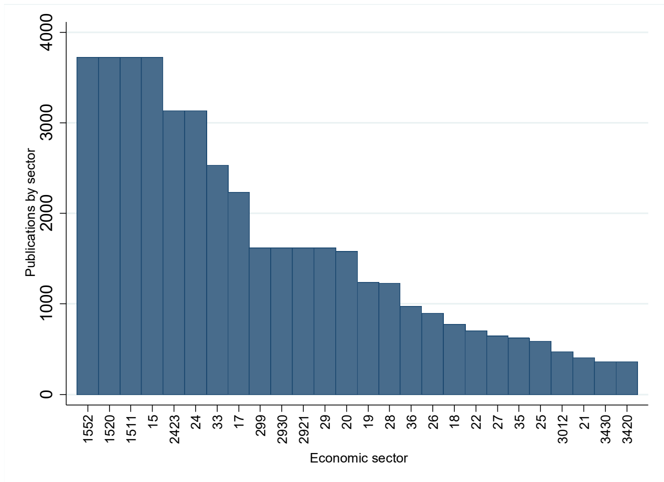
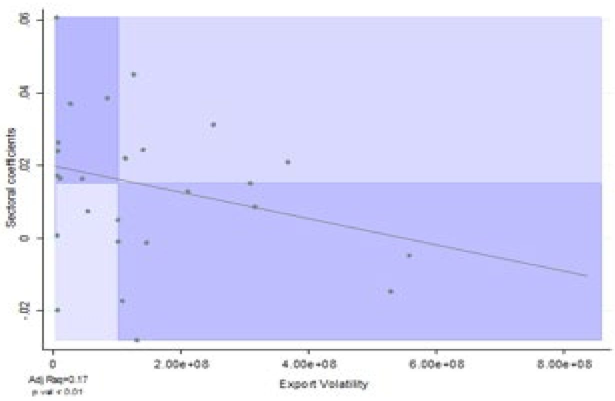
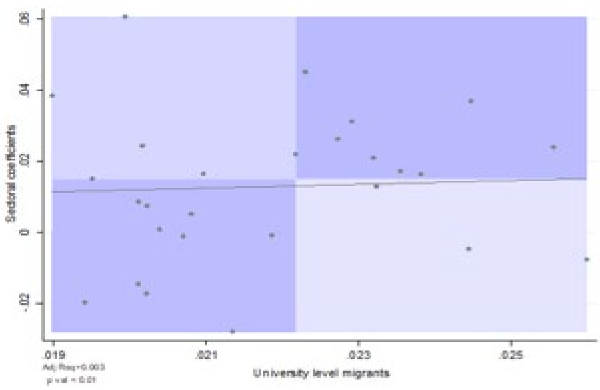


Figure B.4. Correlation between Contextual Factors and Sectoral RD&D Returns

a. Export volatility



b. Immigrants with a university degree



Appendix C. Measurement of Physical Capital Stock

Our strategy to estimate firms' capital stock for the period 2014–16 is described by the following equation:

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

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.

The first term is the average proportion of energy consumption in relation to labor costs (a kind of K/L), for each sector and size group, multiplied by each firm's wage costs. Therefore, if we assume that the relationship between energy costs and wage costs within each sector-size group is stable through time, this multiplication estimates the energy costs of firm *i* at time *t* explained by *existing machinery*.

The second term estimates the average energy use of new equipment (which we assume is equal to the investment in machinery) by sector using information from ENDEI 1, which is then multiplied by each firm's investment in new machinery for innovation.[33] Therefore this second multiplication estimates the energy consumption of the firm due to *new machinery*. Both terms of the sum are expressed in units of energy expenses, which makes the addition possible.

Comparing capital intensity across sectors using energy consumption as a proxy gives reasonable and consistent results with data from both ENDEI 1 and the estimated indicator calculated with equation [3] for ENDEI 2. The most capital-intensive sectors were pharmaceutical, others (which includes cars and petroleum), basic metals, and non-metallic minerals.

Table C.1 presents some descriptive statistics for key variables included in equation [1]. Table C.2 presents their correlation matrix. Labor productivity increases with firm size, as do our proxies for labor, capital, and knowledge factors. Coefficients of variation are larger for RD&D than for other factors. Our estimation of capital stock is not particularly dispersed. Capital stock correlates more tightly with value added per worker than knowledge and labor factors—although none of the correlation coefficients appears to be particularly high, but all of them are significant.

[33] In the cases where wage costs were not reported, we imputed the value of wage costs using the estimated average of this variable for the firm's sector-size group.

Table C.1. Descriptive Statistics of Variables in Equation [1]

Firm size		VA per worker (in 10 thousands)	RD&D per worker (proxy for knowledge stock) (in thousands)	Estimated energy consumption per worker (proxy for capital stock) (in thousands)	Labor
Small	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	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	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

Note: RD&D = research design and development; VA = value added.

Table C.2. Pearson Correlation Coefficients for Variables Included in Equation [1]

	VA per worker	RD&D per worker (proxy knowledge stock)	Estimated energy consumption per worker (proxy capital stock)	Labor
VA per worker	1			
RD&D per worker (proxy knowledge stock)	0.122	1		
Estimated energy consumption per worker (proxy capital stock)	0.274	0.114	1	
Labor	0.141	0.05	0.274	1

Note: RD&D = research design and development; VA = value added.

Appendix D. Considering Firms' Innovative Capacity by Accounting for Strategy and Managerial Skills

We considered whether firms' specific attitudes on such matters as strategy and managerial skills, which proxy firms' innovative capacity, affect the impact that contextual factors have on RD&D returns. For this, we include variables constructed with answers from Sections 2 and 7 of ENDEI 2, which give information on the firm´s attitude toward innovation, its position in the market, and managerial strategy. Interacting these variables with the interaction of RD&D and the contextual variables allows us to see if this interaction is significant for specific types of firms. Given that the firm's susceptibility to the various contextual variables depends on different attitudes that shape its innovative capacity, we chose different specific attitudes that we considered relevant to interact with each contextual factor.

Table D.1. Proxies of Firms' *Innovative Capacity* to Benefit from Contextual Factors, Built from Firms' Strategies, Attitudes, and Managerial Skills, by Contextual Factor of Figure 5

Contextual factor interacted	Proxy of *innovative capacity* to take advantage (or hedge against) contextual factor	
	Name	**Explanation**
STI Policy and Spillovers	STI and SPIL	For "Publications," we use a dummy equal to 1 if the firm relies on academic-specific information sources (Q 7 answers 10, 11, 14, 15). For "Innovation per sector-region," we use a dummy equal to 1 if the firm relies on other firms for information (Question 7 answers 7, 8, 9, 13, 14). These variables are intended to represent the intensity of the firm´s relationship with external information sources. Firms with a stronger relationship will probably benefit more from the supply of scientific knowledge and inter-sectoral spillovers.
Demand	DEM	A variable that indicates whether a firm declares that one of the main motives to innovate were factors related to market demand (Q 7.2, answers 6, 7, 8).
Competition	COMP	A dummy that is equal to 1 if the firm considers itself a technological leader in the market. These firms are expected to be positively affected by competition, as a more competitive environment will push them to increase their innovation activity (Q 2.2, answer 1).
Regulation	REGU	A dummy indicating whether the firm mentioned satisfying regulations and rules as a main motivation for innovation (Q 7.2, answer 11).
Uncertainty	VOLAT	A variable equal to 1 if the firms mentioned macroeconomic uncertainty as an obstacle to innovation (Q 7.3, answer 10).

To introduce these managerial skills, we followed a procedure similar to the one used to select the contextual variables. First, we estimated separate regressions for each group of contextual factors using as a baseline our estimation of column 8 in table A.3. Results can be seen in table D.2.

In column 1 of table D.3, we join the results for all the groups. We include micro-level interactions only when they add new (relevant) information to the results, which is the case of the first four columns of table D.2:[34]

[34] We considered results to be relevant when the inclusion of the firm-specific characteristic allows us to observe heterogenous RD&D returns across different groups of firms. We do not consider the interaction with our regulation variable relevant because it was not statistically significant. Interaction with spillovers and uncertainty measures are not relevant either, given that they are significant for both groups of firms, and the coefficients are not statistically different.

Table D.2. Micro Interactions: Regressions by Groups of Contextual Variables

VARIABLES	(1) STI pol	(2) Spillovers	(3) Demand	(4) Compet	(6) Regul	(7) Uncert
Capital per worker	0.30***	0.30***	0.30***	0.30***	0.30***	0.30***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
RD&D per worker	0.013**	-0.0090	0.016**	0.0048	0.0033	0.012***
	(0.0077)	(0.011)	(0.0063)	(0.0039)	(0.014)	(0.0041)
Labor	-0.27***	-0.26***	-0.26***	-0.26***	-0.26***	-0.26***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Year =2015	0.19***	0.18***	0.19***	0.18***	0.18***	0.18***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Year =2016	0.33***	0.34***	0.35***	0.35***	0.35***	0.35***
	(0.027)	(0.024)	(0.023)	(0.023)	(0.024)	(0.023)
Missing dummy	0.11**	0.10**	0.097**	0.082*	0.089*	0.092*
	(0.047)	(0.045)	(0.048)	(0.047)	(0.047)	(0.048)
STI=0 * Publications	7.009					
	(8.98)					
STI=1 * Publications	45.48***					
	(10.24)					
STI=0* Publications * RD&D p.w	-0.084					
	(0.269)					
STI=1* Publications * RD&D p.w	-0.607***					
	(0.231)					
RD&D p.w *STI =1	0.0039					
	(0.007)					
SPIL=0 *MigUniv		2.79				
		(4.44)				
SPIL=1 *MigUniv		-0.394				
		(2.99)				
SPIL=0 * Inno_sector_region		-0.526				
		(1.85)				
SPIL=1 * Inno_sector_region		6.65***				
		(1.08)				
SPIL=0 *MigUniv * RD&D p.w		1.70**				
		(0.77)				
SPIL=1 *MigUniv* RD&D p.w		0.34**				
		(0.162)				
RD&D p.w * SPIL=1		0.0296				
		(0.0203)				
SPIL=0 *RD&D p.w. * Inno_sector_region		-0.345				
		(0.353)				
SPIL=1 *RD&D p.w. * Inno_sector_region		-0.264				
		(0.166)				
DEM=0* Expo			0.021***			
			(0.0061)			
DEM=1* Expo			0.0070			
			(0.0078)			
DEM=0* RD&D p.w. * Expo			-0.00034			
			(0.00043)			
DEM=1* RD&D p.w. * Expo			0.00088			
			(0.00060)			
DEM=1* RD&D p.w			-0.0097			
			(0.0074)			
COMP=0* Herfindahl				-0.97**		
				(0.41)		
COMP=1* Herfindahl				-1.07		
				(1.03)		
COMP=0* RD&D p.w. * Herfindahl				0.034**		
				(0.014)		

Table C.2 *continued*

COMP=1* RD&D p.w. * Herfindahl				-0.089*		
				(0.050)		
COMP=1* RD&D p.w				0.0069		
				(0.0088)		
REGU=0* FirmEntryExit					0.23	
					(0.66)	
REGU=1* FirmEntryExit					1.30	
					(1.04)	
REGU=0* RD&D p.w. * FirmEntryExit					0.025	
					(0.077)	
REGU=1* RD&D p.w. * FirmEntryExit					0.117	
					(0.157)	
REGU=1* RD&D p.w					-0.022	
					(0.025)	
VOLAT=0* Volatility of financial credits						46.9
						(110)
VOLAT=1* Volatility of financial credits						121
						(130)
VOLAT=0* RD&D p.w * Volat of financial credits						-38.4***
						(14.1)
VOLAT=1* RD&D p.w * Volat of financial credits						-28.4*
						(16.3)
VOLAT=1* RD&D p.w						-0.0043
						(0.0052)
Constant	10.3***	10.6***	10.6***	10.8***	10.6***	10.6***
	(0.42)	(0.39)	(0.37)	(0.39)	(0.39)	(0.38)
Observations	9,246	9,246	9,246	9,246	9,246	9,246
R-squared	0.392	0.392	0.391	0.392	0.390	0.391
Number of ID	3,489	3,489	3,489	3,489	3,489	3,489

Note: COMP = competition; DEM = demand; p. w. = per worker; RD& D = research design and development; SPIL = spillover; STI = science, technology, and innovation; VOLAT = volatility. Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table D.3. Micro Interactions: Joining All Variables

VARIABLES	(2) Joining everything
Capital per worker	0.29***
	(0.032)
RD&D per worker	0.0034
	(0.015)
Labor	-0.27***
	(0.045)
Year =2015	0.19***
	(0.015)
Year =2016	0.32***
	(0.028)
Missing dummy	0.10**
	(0.047)
STI=0* Publications	-0.21
	(9.41)
STI=1* Publications	**31.6*** **
	(10.8)
SPIL=0* Inno_sector_region	0.92
	(1.95)
SPIL=1* Inno_sector_region	**5.00*** **
	(1.13)
Univ Migrations	2.48
	(3.15)
DEM=0* Expo	**0.027*** **
	(0.0072)
DEM=1* Expo	0.0082
	(0.0083)
COMP=0* Herfindahl	**-0.94** **
	(0.39)
COMP=1* Herfindahl	-1.09
	(1.07)
Firm Entry+Exit	0.67
	(0.70)
Credit volat. by sector	107
	(103)
STI=0* RD&D p.w. * Publications	0.065
	(0.30)
STI=1* RD&D p.w. * Publications	-0.65**
	(0.30)
SPIL=* RD&D p.w. * Inno_sector_region	-0.34
	(0.31)
SPIL=1 *RD&D p.w. * Inno_sector_region	-0.14
	(0.19)
RD&D p.w. * MigUniv	**0.32** **
	(0.15)
DEM=0* RD&D p.w. * Expo	-0.00051
	(0.00040)
DEM=1* RD&D p.w. * Expo	**0.0011** **
	(0.00056)
COMP=0* RD&D p.w. * Herfindahl	**0.025** **
	(0.011)
COMP=1* RD&D p.w. * Herfindahl	**-0.091* **
	(0.047)
RD&D p.w. * FirmEntryExit	0.014
	(0.068)
RD&D p.w. * Volat_credit_sect	**-31.1*** **

Table C.3 *continued*

	(11.3)
STI=1* RD&D p.w	0.0079
	(0.0077)
SPIL=1 *RD&D p.w	0.0027
	(0.0095)
DEM=1* RD&D p.w	-0.0084
	(0.0071)
COMP=1* RD&D p.w	0.0048
	(0.0087)
Constant	10.5***
	(0.47)
Observations	9,246
R-squared	0.398
Number of ID (sample size)	3,489

Note: COMP = competition; DEM = demand; p. w. = per worker; RD& D = research design and development; SPIL = spillover; STI = science, technology, and innovation; VOLAT = volatility. Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix E. ENDEI 2 Economic Sectors

ISIC Code (Rev 3)	Sector
15	Food
1511	Meat industry
1520	Dairy products
1552	Wine and other beverages
17	Textile products
18	Wearing apparel
19	Leather
20	Wood
21	Paper
22	Publishing, printing and reproduction of recorded media
24	Chemical products
2423	Pharmaceutical products
25	Rubber and plastic products
26	Other non-metallic minerals
27	Basic metals
28	Other metal products
29	Machinery and equipment
299	Tools and machinery in general
2921	Machinery for Agriculture
33	Medical instruments
35	Other transport equipment
36	Furniture
2930	Equipment for domestic use
3012	Electrical material, radio and TV
3420	Trailers and semi-trailers
3430	Car parts
9999	Others, includes tobacco (16), cars (341), oil (23), and recycling (37)

Note: ENDEI = second round of the Employment and Innovation Dynamics National survey; ISIC (Rev 3) = third revision of the International Standard Industrial Classification of All Economic Activities.

Appendix F. Implications for Research and Data Collection

Making Micro Data Sets More Accessible

Micro databases in Argentina are rarely available for research. Although several waves of innovation surveys have been produced since 1992, micro-data were made publicly available only after the Labor and Employment Ministry and the Science, Technology and Productive Innovation Secretariat produced the Employment and Innovation Dynamics National (ENDEI) survey (2010–12). Public dissemination required an effort from these organizations to guarantee confidentiality. This was an important institutional innovation, as it was the first time that economic information was made available at the micro level.

It would be very useful to follow the same procedures for previous innovation surveys (ENIT, National Survey on Innovation and Technology Behavior) managed by the National Institute of Statistics and Censuses, INDEC. A panel with innovation data could be built beginning with the early 1990s with these data sets. Similar recommendations could be made for industrial surveys. In contrast to other countries in the region, in Argentina there is no access to valuable information that could be used for different research purposes, such as providing empirically based policy recommendations.

Building Panels

Panel databases need to be built. Neither ENIT nor ENDEI was built to be matched over time. In fact, the questionnaires are not the same—not even between ENDEI 1 and ENDEI 2. Data are not matched. The resulting panel, if/when matched, will not be representative either at either the sector or regional level because of differences in sampling procedures for each wave. This complicates the use of panel-data econometric techniques, which are advisable to control for biases originated by time-invariant omitted variables.

Matching Databases

It is also necessary to be able to match different databases such as innovation and industrial surveys and administrative data, such as those produced by Customs, the revenue service (AFIP), and the social insurance agency (ANSES), and offer these matched databases for research.

One particular database that would be useful to match is produced by FONTAR, the main program supporting firm innovation offered by the National Agency for Science and Technology Promotion. FONTAR, like ENDEI, depends on the Secretary of Science, Technology and Productive Innovation. FONTAR includes different instruments, as tax credits, subsidized loans, and matching grants. The FONTAR database has information for firms that have applied to FONTAR since 2008. All applicants are requested to fill out an innovation survey, which makes it possible to construct groups for beneficiaries and non-beneficiaries to be used in impact assessments. Although the data are available, access is restricted and has been allowed only for internal evaluation or when FONTAR funders requested it (see Pereira and Suárez 2018, Arza and Vázquez 2014, 2015).

Providing More and Better Sectoral, Regional, and More Aggregated Information

There is a serious lack of sectoral and regional data in Argentina. For example, there is no consistent information on value added disaggregated by sector-province. The latest data available are for 2004. In addition, there is no sufficiently disaggregated information on sectoral value added at the national level over time (at the ISIC 3-digit level). There is very little information about public policy supporting industrial sectors, and even less at the regional/provincial levels. For example, there are no data on the public budget organized by sectoral activities over time that could be used to assess the impact of public budget expenditures on firms' productivity.

Finally, there is very little information about institutional quality in Argentina (for instance measures of corruption, or "doing business" surveys with enough disaggregation across sectors and regions).

Improving Formats

Certain information is available but only in a very unfriendly format for use in research. For example, international trade data by province are accessible, but must be downloaded in a very fragmented fashion. Similarly, for export/import tariffs or nontariff measures, some information is available, but is presented in an unsuitable way for analysis. This information can be accessed only by entering the product code in a webpage, while no databases are available that summarize the export tariffs for a set of products. Finding data on historic trade tariffs is also extremely complicated.

In addition, it would be good to merge different databases on science and research. For instance, information about agreements signed at liaison offices at universities or National Scientific and Technical Research Council (CONICET) is available only in an unfriendly format. Combining that information with bibliometric information, could be used to build information on knowledge networks across disciplines and geographic locations. This could yield useful insights on regional/sectoral competitiveness and help measure the impact of public support to research activities in the country.

Recommendations Regarding ENDEI

Argentina lacks a measure of capital stock at either the firm or sectoral level. Because panels are not built, it is not possible to use methods of permanent inventory (that is, using firms' investment in physical assets over time). It is therefore particularly important that innovation surveys include variables that could be used as proxies for capital stock, such as energy consumption or investment in physical assets. In ENDEI 2, both measures presented measurement errors and therefore could not be used.

For comparisons across countries, it would be good to follow international guides, such as the Oslo Manuals. In the case of ENDEI, some questions do follow those guidelines (such as innovation expenditures) but others do not (such as barriers to innovation).

Regarding qualitative information, we recommend using Likert scales for each category. This would allow researchers to assess each category independently within a question, instead of asking respondents to rank order (or to choose a number of relevant) different options in a list, as is done in ENDEI 2 in questions 2.1 and 2.2.

One question included in the OSLO manual that used to be part of ENIT questionnaire asks about the importance of different research fields for firms' innovation activities, using the Likert scale. This question is useful to assess to what extent public support to scientific fields matches firms' demand of scientific knowledge. It is not included in ENDEI questionnaires. It might worth reassessing its relevance for future surveys.

Finally, it would be very useful to administer innovation surveys for firms in the service sector, given the importance this sector has for national value added and employment.