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CHAPTER 2

Innovation Dynamics and Productivity: Evidence for Latin America

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Although the GDP per capita of most Latin American countries has grown rapidly since 2003, it still significantly lags the levels of industrialized countries. Further, productivity, the main driver of long-term economic growth, has expanded at a lower rate than the world's technological frontier (IDB 2010). Thus, improving productivity is the main challenge for Latin America. But what creates productivity growth? Economies are becoming more knowledge based, and innovation is a key driver of national competitiveness, development, and long-term economic growth. At the firm level, innovation—the transformation of ideas into new products, services, and production processes—leads to a more efficient use of resources, creating sustainable competitive advantages. At the same time, innovation leads to

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completely novel sectors, where new firms start operating and new production routines are generated. Change in the production structure is what increases specialization and productivity growth (Katz 2006) as well as the gradual expansion of more knowledge-intensive production activities. Hence, innovation is essential to spur economic growth and to raise living standards.[1] At the macro-level, research and development (R&D) spending, innovation, productivity, and per capita income reinforce each other and lead to sustained long-term growth (Hall and Jones 1999; Rouvinen 2002).

Evidence of the relationship between R&D, innovation, and productivity has been found in studies of industrialized countries (Griffith et al. 2004; Griffith et al. 2006; OECD 2009; Mairesse and Mohnen 2010). Investing in innovation can have substantial economic payoffs. Firms that invest in innovation are better equipped to introduce technological advances and tend to have higher labor productivity than those that do not. Crespi and Zuñiga (2012) reported that productivity gaps in the manufacturing sector between innovative and non-innovative firms are much higher in Latin America than in industrialized countries. For the typical country in the European Union, the productivity gap is 20%, while for the typical Latin American country it is 70%. Thus, Latin America has great potential to benefit from investment and policies that foster innovation.

One of the most important limitations of previous research on innovation in Latin America was the absence of harmonized and comparable indicators across the different countries, which seriously limited the possibility of inferring policy conclusions that were not affected by country specifics with respect to data quality and coverage.[2] Also, most of this research focuses on estimating firm-level correlations without attempting to identify market failures or other limitations that harm innovation investment. In this chapter, a wide range of innovation indicators are analyzed in order to describe the innovation behavior of manufacturing firms in Latin America using the World Bank Enterprise Survey (WBES) database.[3] The authors' objective is to understand the main characteristics of innovative firms in Latin America and to gather new evidence regarding the nature of the innovation process in the region. The next section of this chapter reviews the main findings in the literature on determinants of innovation in both industrialized and developing countries. Using various indicators, the third section presents statistics about the innovation performance of Latin American firms. The ways that innovation relates to firm characteristics in Latin America are explored using a structural model approach to untangle the determinants of innovation investment and performance and productivity at the firm level. The fourth section extends the model to gather some evidence regarding the prevalence of spillover effects and the extent to which there is an important heterogeneity regarding returns on innovation.

Literature Background

Innovation is fundamental to catching up economically and raising living standards. Evidence demonstrates a virtuous circle in which R&D spending, innovation, productivity, and per capita income mutually reinforce each other and lead to long-term, sustained growth rates (Hall and Jones 1999; Rouvinen 2002; Guloglu and Tekin 2012) and may foster job creation (Vivarelli 2013).[4] R&D is a source of direct and indirect advantages for firms. There is convincing evidence that shows positive linkages between R&D, innovation, and productivity at the firm level in industrialized countries (Griffith et al. 2004; Griffith et al. 2006; OECD 2009; Mairesse and Mohnen 2010; Mohnen and Hall 2013). In addition, R&D contributes to firms' absorptive capacity, a fundamental prerequisite for learning by doing. Internal R&D supports better identification of the value of external technology, its assimilation, and its use while expanding the stock of knowledge of firms (Cohen and Levinthal 1989; Griffith et al. 2004). Hence, strengthening in-house technological capabilities induces knowledge spillovers by acquiring machinery and equipment and interacting with other firms.

We note that an important strand of the literature deals with country- or sector-level information. However, considering the innovation results from the investment decisions made by individual firms, the microeconomic analysis has the potential to enlighten the foundations of the correlations found at the macro-level. Taking advantage of innovation surveys, Crépon et al. (1998) were the first to empirically integrate these relationships in a recursive model (Crépon–Duguet–Mairesse [CDM] model), allowing innovation inputs (R&D investment) to be estimated. Their findings for France corroborated the positive correlation between firm productivity and higher innovation output, even controlling for the skill composition of labor. They also confirmed that a firm's decision to invest in innovation (R&D) increases with its size, market share, and diversification, and with the demand-pull and technology-push forces.

Building on the CDM model, a new wave of studies that exploited innovation surveys emerged and reported similar results for other industrialized countries. Using different indicators of economic performance, such as labor productivity, multifactor productivity, sales, profit margins, and market value, studies repeatedly showed that technological innovations (product or process) lead to superior economic performance for the firm (Loof and Heshmati 2002; Loof et al. 2003; Janz et al. 2004; Van Leeuwen and Klomp 2006; Mohnen et al. 2006). This literature also highlights the fact that firm heterogeneity is important to explain innovation activities and their effects on firm performance, and must be controlled for in empirical estimations (Hall and Mairesse 2006; Mairesse and Mohnen 2010; and Chap. 1 of this book). Further, the correlation between product innovation and productivity is often higher for larger firms (Griffith et al. 2006; OECD 2009) and, as expected, in most countries the productivity effect of product innovation is larger in manufacturing than in services (OECD 2009). In addition, a positive association is consistently confirmed between R&D and innovation outcomes. Firms that invest more intensively in R&D are more likely to develop innovations, once endogeneity is corrected for and controlling is done for firm characteristics such as size, affiliation to group, or type of innovation strategy.

In contrast, evidence with regard to the ability of firms in developing economies to transform R&D into innovation is not as conclusive. This heterogeneity could be explained by the fact that firms in developing countries are too far from the technological frontier and incentives to invest in innovation are weak or absent (Acemoglu et al. 2006). In this vein, a positive association between R&D, innovation, and productivity was found for new industrialized countries such as South Korea (Lee and Kang 2007), Malaysia (Hegde and Shapira 2007), Taiwan (Aw et al. 2008), and China (Jefferson et al. 2006). By investing in R&D and human capital, these countries managed to narrow their distance from the best practices. However, in many Latin American economies, firms' innovations consist of incremental changes with little or no impact on international markets, and are mostly based on imitation and technology transfer, such as acquisition of machinery and equipment and disembodied technology (Anlló and Suárez 2009; Navarro et al. 2010). In many cases, R&D is prohibitive financially, and considering the human capital needed, its materialization could require long time horizons (Navarro et al. 2010).

There is evidence that higher levels of investment in innovation (notably in R&D) lead to a higher propensity to introduce technological innovation in firms in Argentina (Chudnovsky et al. 2006) and Brazil (Correa et al. 2005; Raffo et al. 2008), but research does not support this relationship for Chile (Benavente 2006) or Mexico (Perez et al. 2005). The results regarding the impact of innovation on labor productivity are equally inconclusive for Latin American firms. Raffo et al. (2008) found a significant impact of product innovation for Brazil and Mexico but not for Argentina, though

Perez et al. (2005), Chudnovsky et al. (2006), and Benavente (2006) failed to find any significant effect of innovation on firm productivity (measured as sales per employee) in Argentinean and Chilean firms. Hall and Mairesse (2006) suggested that the lack of significance of innovation in productivity in developing countries may reflect the very different circumstances surrounding innovation in these economies compared to Western Europe, and they suggested evaluating the effects over longer periods of time (for evidence from Chile, see Benavente and Bravo 2009).[5]

One important pitfall of previous research is related to the lack of homogeneous and comparable data across the different countries in the Latin American region, which may be a factor underlying this heterogeneity. Differences in sampling methodologies, questionnaire design, and data processing for the existing innovation surveys seriously affect the comparability of the results. Crespi and Zuñiga (2012) performed the first comparative study to examine the determinants of technological innovation and its impact on firm labor productivity in manufacturing firms across Latin American countries (Argentina, Chile, Colombia, Costa Rica, Panama, and Uruguay). The authors used micro-data from innovation surveys but the same specification and identification strategy. This exercise showed more consistent results. Specifically, firms that invested in knowledge were more able to introduce technological advances, and those who innovated exhibited superior labor productivity than those who did not. Yet, firm-level determinants of innovation investment are still more heterogeneous than in Organisation for Economic Co-operation and Development (OECD) countries: cooperation, foreign ownership, and exporting increase the propensity to invest in innovation in only half of the countries. At the same time, a firm's linkages and use of different sources of information for innovation activities (scientific and market) have little or no impact on innovation efforts. This illustrates the weak articulation that characterizes national innovation systems in the region. The results regarding productivity, however, highlight the importance of innovation for firms to improve economic performance and to catch up.

Taking these efforts a bit further, the contribution of this chapter is twofold. First, we make use of a homogeneous questionnaire and dataset, which allows us to make more easily generalizable conclusions. Second, most of the previous research on the micro-determinants of innovation and their impacts on productivity deal with structural determinants and, although these results are useful for policy design, they are insufficient in that they are not directly linked to market failures. Our research extends previous analyses by looking at the impacts of spillovers on the determinants of innovation investments.

Research Questions and Conceptual Framework

This chapter aims to gather new evidence regarding the determinants of innovation investments—in particular R&D—in LAC and their impacts on productivity at the firm level. More specifically, we address the following research questions:

1. What are the determinants of innovation investments in LAC?
2. What are the returns on innovation investments?
3. What are the impacts of innovation outputs on productivity?
4. Is there heterogeneity in the effects of investments in innovation on productivity?
5. Is there any evidence of spillovers that could guide policy design and analysis?

In this chapter, we apply the CDM model to estimate the determinants of innovation (R&D) and its impact on total factor productivity (TFP). The CDM model has three stages:

1. Firms decide whether or not to invest in R&D activities and how much to invest.
2. Knowledge (technology) is produced as a result of this investment ("knowledge production" function) (Griliches 1979; Pakes and Griliches 1980).
3. Output is produced using new knowledge (technological innovation) along with other inputs.

Thus knowledge is assumed to have a direct impact on firm economic performance, generally expressed by TFP. In addition to firm characteristics, the model includes external forces acting concurrently on the innovation decisions of firms and indicators of demand-driven innovation (i.e. environmental, health, and safety regulations), technological push (i.e. scientific opportunities), financing (i.e. R&D subsidies), and spillovers.

The CDM model is intended to deal with the problem of selectivity bias[6] and endogeneity in the functions of innovation and productivity.[7] The model can be written as follows.

Let $i = 1 \ldots N$ index firms

Equation (2.1) accounts for firms' innovative efforts IE_i^*:

$$IE_i^* = z_i \beta + e_i \tag{2.1}$$

where IE_i^* is an unobserved latent variable, z_i is a vector of determinants of innovation effort, β is a vector of parameters of interest, and e_i is an error term. We proxy firms' innovative effort IE_i^* by their (log) expenditures on R&D activities per worker denoted by IE_i only if firms make (and report) such expenditures. Thus we can only directly estimate equation (2.1) at the risk of selection bias (Griffith et al. 2006). Instead, we assume the following selection equation describing whether the firm decides to do (and/or report) innovation investment or not:

$$ID_i = \begin{cases} 1 \; if \; ID_i^* = w_i\alpha + \varepsilon_i > c, \\ 0 \; if \; ID_i^* = w_i\alpha + \varepsilon_i \le c \end{cases} \tag{2.2}$$

where ID_i is a binary endogenous variable for innovation decision that is equal to zero for firms that do not invest in innovation and one for firms investing in innovation activities; ID_i^* is a corresponding latent variable such that firms decide to do (and/or report) innovation investment if it is above a certain threshold level c, and where w is a vector of variables explaining the innovation investment decision, α is a vector of parameters of interest, and ε is an error term. Conditional on firm i doing innovation activities, we can observe the amount of resources invested in innovation (IE) activities, and write:

$$IE_i = \begin{cases} IE_i^* = z_i\beta + e_i \; if \; ID_i = 1 \\ 0 \; if \; D_i = 0 \end{cases} \tag{2.3}$$

Assuming the error terms e_i and ε_i are bivariate normal with zero mean, variances $\sigma_\varepsilon^2 = 1$ and σ_e^2 and correlation coefficient ρ_e, we estimate the system of equations (2.2) and (2.3) as a generalized Tobit model by maximum likelihood.

The next equation (2.4) in the model is the knowledge or innovation production function:

$$TI_i = IE_i^* \gamma + x_i \delta + u_i \tag{2.4}$$

where TI_i is knowledge outputs by technological innovation (introduction of a new product or process at the firm level), and where the latent innovation effort, IE_i^*, enters as an explanatory variable, x_i is a vector of other determinants of knowledge production, γ and δ are vectors of parameters of interest, and u_i is an error term. The last equation (2.5) relates innovation to productivity. Firms produce output using a technology represented by a Cobb–Douglas function with labor, capital, raw materials, and knowledge as inputs as follows:

$$y_i = \pi_1 k_i + \pi_2 m_i + \pi_3 TI_i + v_i \tag{2.5}$$

where output y_i is labor productivity (log of sales per worker), k_i is the log of physical capital per worker (measured by physical investment per worker), m_i is the log of raw materials and intermediate goods per worker, and TI_i is an explanatory variable that refers to the impact of technological innovation on productivity levels.[8]

In all equations, we control for unobserved industry characteristics by including a full set of two-digit ISIC code dummies. We control for idiosyncratic characteristics of each national innovation system by including a full set of country dummies. We also control for firm size in all equations but the R&D investment equation (2.2), because R&D investment intensity is already implicitly scaled for size. As this recursive model does not allow for feedback effects between equations, we implement a three-step estimation routine. First, we estimate the generalized Tobit model (equations 2.2 and 2.3). Second, we estimate the innovation function as a probit equation using the predicted value of (log) innovation expenditure as the main explanatory variable instead of reported innovation efforts, thus correcting for potential endogeneity in the knowledge production equation. Last, we estimate the productivity equation using the predicted values from the second step to take care of the endogeneity of TI_i in equation 2.5.

As in other studies using innovation survey data, our estimation of the CDM model suffers from several measurement shortcomings. First, both Griliches (1979) and Crépon et al. (1998) used patent data as indicators of technological innovation; however, patent information is almost irrelevant in developing countries where only a very small set of firms innovate at the frontier level. Instead, we use a self-reported innovation output variable, which is qualitative information and much noisier than patent statistics. This type of innovation measurement is very subjective because firms are asked to declare whether they innovated or not (introduced a product or a process), and what one firm considers an innovation may not be the same as what other firms consider innovation. Second, the original knowledge production models relate knowledge production to knowledge capital, or the stock of R&D (or innovation investment). As we have cross-sectional information, we can only use the investment in knowledge in the previous year(s), inducing a measurement error in knowledge capital.[9] These are typical limitations encountered when analyzing R&D or innovation activities using innovation survey data; many previous studies share these limitations.

Consistent with evidence from developed countries, we also use R&D as the main dependent variable in equations 2.2 and 2.3. This decision is mostly data driven. According to Crespi and Zuñiga (2012), a better dependent variable could have been total innovation investment, which also includes training and investment in know-how and technology transfer. Unfortunately, the data is not detailed enough to be able to produce information on these additional sources of innovation investment. However, R&D plays a privileged role as part of the mechanism that leads to creating, adapting, and absorbing new ideas and technological applications (Griffith et al. 2004). Including R&D as the main dependent variable enables a better identification, assimilation, adaptation, and exploitation of external know-how (Cohen and Levinthal 1989), augmenting the impact of innovation on productivity. From a policy perspective, R&D consists of an intangible investment and, as such, the most likely to be affected by market failures such as externalities or coordination failures.

In line with previous studies, we not only use technological innovation as a dependent variable but we also estimate separate versions of equation 2.4 for each type of innovation output (product or process). This allows us to explore whether there are different returns for each different class of innovation investment. Lastly, in line with Griffith et al. (2006) and Crespi and Zuñiga (2012), we estimate the CDM model not only for innovative firms but for all firms. Accordingly, we estimate steps (1) and (2) based on reported innovation investment activities. Then, we use the relationship between observable characteristics and innovation spending to predict the likelihood of investing for all firms as a proxy for innovation effort in the knowledge production function. In turn, equation 2.4 (technological innovation) and equation 2.5 (productivity) are estimated for all firms. In equation 2.5, we include the predicted value of technological innovation. There are two reasons for using this estimation strategy.

First, the survey does not have a filter and most of the questions are asked to all firms. Second, the model assumes that all firms exert some kind of innovative effort but that not all firms report this activity. The output of these efforts produces knowledge and, thus, enables us to have an estimate of innovation efforts for all firms.[10] Of course, this strategy is debatable because the approach assumes that innovation efforts and innovation output for firms that do not report innovation activities is the same as for reporting firms. Given that we use estimated independent variables, we need to correct for the standard errors in equations 2.4 and 2.5, which we do by bootstrapping.

Dataset and Empirical Implementation

For this study, we use the WBES, which are firm-level surveys of a representative sample of the private sector of an economy. The World Bank has been conducting these surveys since 2000 for key manufacturing and services sectors in every region of the world. In each country, businesses in the cities or regions of major economic activities are interviewed. The WBES surveys formal (registered) companies with five or more employees, but excludes firms that are wholly government owned. The sampling methodology is stratified random sampling, where firm size, business sector, and geographic region within a country are used as strata. Typically 1200 to 1800 interviews are conducted in larger economies, 360 interviews in medium-sized economies, and 150 interviews in smaller economies.

We use the data from the innovation module of the WBES 2010, which excluded the service sector. As a result, our analysis only covers manufacturing firms for 17 Latin American countries.[11] In addition to descriptive and performance variables, the surveys include data on a range of innovation activities, such as developing technological products, processes, and non-technological innovation (e.g. managerial, organizational, and marketing practices). A firm is considered an innovator if it has introduced a product or a process innovation in the previous three years (2007–2009). These innovations could be new to the firm or new to the market.

Following Mohnen et al. (2006), we eliminate all firms with sales growth over 250% and lower than 60% in the 2007–2009 period, and firms that reported a ratio of R&D spending to sales higher than 50%. To maintain consistency with the sample design of the survey, we drop firms that reported less than five employees, and we only consider sectors in countries that have at least five firms surveyed. After we apply this data