The Effects of Knowledge Spillovers through Labor Mobility*

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Abstract

This paper estimates the effects of knowledge spillovers on firms' long-term performance and workers' wages. For this purpose, we use the participation in an innovation support program as an exogenous shock to the knowledge stock of non-participant firms. We pinpoint the knowledge diffusion process by tracking the mobility of skilled workers among firms. Combining an employer-employee panel dataset that contains the whole population of firms and workers in Argentina for the period 1998-2013 with administrative data from the FONTAR program, we track the mobility of workers from participant to non-participant firms. To estimate the effect of spillovers we use the panel structure of the dataset using Lag Dependent Variable (LDV) models. We find that firms that hired skilled workers from participant firms increased employment (in addition to the workers from participant firms), the average wage they pay, their exporting probability, and the value of their exports. Consistent with the hypothesis that those effects are due to newly acquired productive knowledge, we provide evidence showing that the effects were driven by firm-level productivity improvements. Finally, we show that a wage premium is paid to skilled workers exposed to the program either by participant (to retain) or non-participant firms (to acquire) depending on the concentration level of the industry of reference. This finding further confirms the hypothesis that valuable productive knowledge is generated through the program and that this knowledge is more extensively diffused in less concentrated industries.
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1 Introduction

Knowledge and knowledge spillovers have been shown to play a key role in the growth of countries (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992; Parente and Prescott, 1994).[1] The lack of appropriation caused by the spillovers, on the other hand, is one of the main reasons why firms' investments in innovation activities tend to be lower than the socially optimum value. Because innovators cannot fully appropriate the benefits of their investment in innovation activities, the private return of the investment in innovation is often lower than its social return,[2] a gap that provides a key justification in favor of policies that foster investment in innovation (Crespi, Maffioli, and Rasteletti, 2014). Although a broad consensus has been reached on the relevance of knowledge spillovers, how to properly identify and measure them remains an open question.

As pointed out by Syverson (2011), any attempt to identify spillovers has to deal with two fundamental challenges. The first one is the so-called "reflection problem" (Manski, 1993);[3] correlated behaviors among specific groups of firms can be a sign of knowledge spillovers, but they can also simply reflect the effects of unobserved third factors. For this reason, the estimation of knowledge spillovers would require the identification of an exogenous source of variation in the knowledge stock for a subset of firms and a clear understanding of how the firm's behavior may respond to such variation.

The second challenge is related to the precise tracking of this behavioral response. Relationships between firms are not always easy to identify, more so those implying some level of knowledge sharing. Various proxies have been used to identify potential knowledge-sharing relationships among firms. These include geographical proximity (Audretsch and Feldman, 1996; Anselin, Varga, and Acs, 1997; Fosfuri and Ronde, 2004), distance in the technological space (Jaffe, 1986), and interindustry linkages (Bernstein and Nadiri, 1989). In other cases, more specific measures of relationships were adopted. These include measures of provision of goods and services (Bonte, 2008), equity investments (Aitken and Harrison, 1999; Javorcik, 2004), common participation in associations and consortia (Gilbert, McDougall, and Audretsch, 2008), patent citations (Henderson, Jaffe, and Trajtenberg, 1993; Thompson and Fox-Kean, 2005; Murata, Nakajima, and Okamoto, 2014), and labor mobility (Rao and Drazin, 2002; Fosfuri, Motta, and Ronde, 2001; Kim and Marschke, 2005; Görg and Strobl, 2005; Moen, 2005; Boschma, Eriksson, and Lindgren, 2009; Maliranta, Mohnen, and Rouvinen, 2009; Balsvik, 2011; Poole, 2013; Stoyanov and Zubanov, 2012).[4]

We propose an empirical strategy to measure knowledge spillovers that deals with both challenges. First, we use the participation of a sub-set of firms in an innovation support program −the Argentinian Technological Development Fund (FONTAR) program− as a variation in the knowledge stock that is exogenous to firms that did not participate in the program. An increasing amount of evidence has shown that these programs induce "additional" knowledge generating efforts in their beneficiaries.[5] For instance, various studies have found that firms that receive the support of

[1]For a survey of the literature on growth and spillovers see Jones (2005).

[2]Since the seminal works by Nelson (1959) and Arrow (1962), knowledge has been regarded as a nonrival and nonexcludable good. If knowledge does indeed have these properties, then a firm's rivals may be able to free-ride on its investments. These spillovers may create a wedge between private and social returns and disincentive private investment in knowledge production.

[3]In Manski (1993)'s words: "the 'reflection' problem that arises when a researcher observing the distribution of behavior in a population tries to infer whether the average behavior in some group influences the behavior of the individuals that comprise the group. The term reflection is appropriate because the problem is similar to that of interpreting the almost simultaneous movements of a person and his reflection in a mirror. Does the mirror image cause the person's movements or reflect them? An observer who does not understand something of optics and human behavior would not be able to tell".

[4]These studies are some examples, though by no means it is meant to be a comprehensive accounting.

[5]See, for instance, Hall and Maffioli (2008), and Hall and Lerner (2010).

technology development funds such as the FONTAR implement R&D projects that they would not have undertaken in the absence of the public intervention. More specifically, Chudnovsky, López, Rossi, and Ubfal (2006) and Binelli and Maffioli (2007) found that the actual FONTAR program increased the investment in R&D of participant firms. Based on this evidence, one can assume that the FONTAR program is a credible source of exogenous variation in the knowledge stock for firms that did not directly receive its support.

Second, we use labor mobility to track potential knowledge sharing between the subset of firms participating in the program and other, non-participating firms. The ability to track the mobility of every worker exposed to the program allows us to precisely define the specific mechanism through which knowledge diffusion occurs. This channel seems to fit particularly well in the case of a program such as FONTAR, which focuses on fostering the generation of knowledge by the participant firms. A good part of this knowledge is in fact captured by the human resources operating within the beneficiary firms during the execution of the FONTAR supported project. Therefore, spillovers occur when these workers move to non-participant firms (hereinafter receiving firms) carrying with them part of the knowledge generated by the participating firms.

Our findings provide evidence of knowledge spillovers and confirm the hypothesis that the benefits of knowledge creation are not fully appropriable by innovative firms. We find that receiving firms grew faster and increased their productivity by hiring qualified workers exposed to the innovation project supported by the FONTAR program. More specifically, our estimates show that receiving firms grew more in terms of number of employees when compared to the control group. Receiving firms also clearly improved their productivity as they increased their survival probability, improved their exporting profile −both in terms of probability of exporting and in terms of value of exports− and the average wage they pay to their employees.

Looking for further evidence of the relevance of the knowledge acquired by workers exposed to the FONTAR program, we estimated the effect at the worker level. Our estimates confirm that these workers actually received a wage premium, whether they stayed at the beneficiary firm or they moved to another firm. This finding confirms that by being exposed to the program, workers acquired valuable productive knowledge for firms willing to pay for it and that this willingness to pay varies accordingly to the level of competition in the market of reference. More specifically, in relatively less concentrated markets non-beneficiary firms are willing to pay a wage premium to acquire such workers higher than the wage premium beneficiary firms would pay to retain them. However, when the market is concentrated, beneficiary firms are willing to pay a higher premium than non-beneficiaries to prevent these workers from being hired by a competitor who could threaten their market position.

To estimate these effects, we use a lagged dependent variable model that allows us to compare firms with a similar evolution before they hire skilled workers from the participant firms (or receive the FONTAR support). Our analysis is based on a unique database. Specifically, we use a linked employer-employee dataset for the population of formal Argentinian firms and their employees. The dataset contains firm-level information on firms' age, location, industry, type of society, whether the firm is multinational, employment, wages, and export behavior between 1998 and 2013. At the worker level, it contains information about wage, tenure at the current firm, age, and gender.

This paper contributes to the existing literature in several ways. First, it proposes a clear and precise identification of the specific mechanisms behind the occurrence of knowledge spillovers. To best of our knowledge, this is the first paper that solves the two main issues in the identification of knowledge spillovers by exploiting both an exogenous shock of variation in the knowledge stock due to firms' participation in an innovation program and the labor mobility for a precise tracking of knowledge sharing between firms. Second, it credibly estimates the magnitude of these knowledge spillovers on firms' long-term performance and on workers' wages. Third, it confirms the basic justification of innovation policy, i.e. the positive externalities due to knowledge diffusion.

The rest of the paper is organized as follows. Section two presents the analytical framework. Section three describes the datasets. Section four discusses the empirical strategy. Section five shows the estimation results. Finally, section six concludes.

2 Analytical framework

2.1 A simple framework

As Syverson (2011) pointed out, the estimation of knowledge spillovers requires some sort of shock in the knowledge endowment that is exogenous to the firms benefiting from these spillover effects. The existence of a public program that supports the implementation of innovation projects by a limited number of firms provides a quite favorable conceptual framework for this estimation.

Suppose that in period t there is a knowledge shock because some firms participate in a public program that allows them to carry out R&D activities and innovation projects that would not have been feasible in the absence of the program. Let's call these firms participating in the public program as F firms. Due to the participation in the public program employees of F firms, especially skilled workers, acquire knowledge related to the design and implementation of the innovation. Assuming that the public program selects projects that are at least "new to the market", this new knowledge is valuable both to their current employer and to the market of reference.[6] Let's assume skilled workers of firm F acquire the level τ of knowledge during the innovation process. These workers will be called C. This knowledge increase is exogenous for those firms that do not participate in the program.

In the next period, C workers can either stay with firm F or move to a new firm. Those firms that may hire skilled workers from firm F are called R. Given that firms' knowledge is partially embedded in its human resources −especially in the skilled workers− part of F's knowledge stock is carried to the new workplace when skilled workers move to other firms.[7] Under the assumption that skilled workers are at least partially aware of the value of what they have learned during the innovation process, they might seek compensation for the new acquired knowledge either from their current employer or from the market.[8]

For simplicity, we assume the workers' utility function depends only on their wages and not on mobility costs. Therefore, the workers will work for the firm that offers them the highest wage.

If the workers engage in a negotiation with a new potential employer (R firms), the new employer needs to pay more than the wage the workers are receiving at firm F, $w^F(\tau)$. Let's assume that the value in terms of production that firm R gets by hiring the worker from firm F is $f^R(\tau)$. A necessary condition for firm R being willing to hire the workers is $f^R(\tau) - w^F(\tau) > 0$, i.e. firm R must gain some surplus at the minimum wage the worker is willing to accept in order to move. Assuming that the worker and the R firm divide the surplus according to a Nash bargaining mechanism, the wage of the worker if hired by the R firm will be given by

$$w^R(\tau) = w^F(\tau) + \beta^R(f^R(\tau) - w^F(\tau)), \tag{1}$$

where β^R is the negotiation power of the worker with the firm R.

[6] As we will discuss in sub-section 2.2, this is the case for the FONTAR program.

[7] Several studies have shown how job mobility of skilled workers facilitates the dissemination of embodied tacit knowledge (Almeida and Kogut, 1999; Maskell and Malmberg, 1999; Cooper, 2001; Power and Lundmark, 2004). In the case of a program such as the FONTAR, the selection criteria also includes the presence of skilled employees.

[8] Obviously firms may try to prevent this by offering initial salaries that already include the market value of the knowledge that workers are expected to acquire during the process, though such value is not easily predictable by the firm.

Similarly, the wage firm F has to pay if the workers engage in a negotiation with their current employer (and the value in terms of production that firm F gets by retaining the worker is $f^F(\tau)$) is given by

$$w^F(\tau) = w^R(\tau) + \beta^F(f^F(\tau) - w^R(\tau)), \tag{2}$$

where β^F is the negotiation power of the worker with firm F. In this case, the necessary condition is given by $f^F(\tau) - w^R(\tau) > 0$.

The worker moves from firm F to firm R if $w^R(\tau) > w^F(\tau)$, i.e.

$$w^F(\tau) + \beta^R(f^R(\tau) - w^F(\tau)) > w^R(\tau) + \beta^F(f^F(\tau) - w^R(\tau)). \tag{3}$$

If we assume the worker stays in firm F if s/he gets the same wage that firm R would offer, firm F would not pay a wage higher than $w^R(\tau)$, therefore the wage firm F would offer is $w^R(\tau)$. Consequently, we can substitute $w^F(\tau)$ in equation (3) by the maximum wage firm F would be willing to pay and see under which conditions firm R is willing to pay more, i.e.

$$f^R(\tau) - w^R(\tau) > \frac{\beta^F}{\beta^R}(f^F(\tau) - w^R(\tau)). \tag{4}$$

Hence, the worker will move to firm R if the surplus at wage $w^R(\tau)$ at that firm is larger than $\frac{\beta^F}{\beta^R}(f^F(\tau) - w^R(\tau))$. The larger the contribution of the worker to the production of firm R and the higher the negotiating power of the worker with that firm, the higher the probability that the worker moves to firm R. On the other hand, the higher the contribution of the worker to firm F and the higher its negotiating power with that firm, the more likely the worker will stay with firm F.

Note that firm F will not compete for the worker by paying $w^R(\tau)$ only if $f^F(\tau) - w^R(\tau) < 0$. If that is the case, the wage firm R would offer is $f^F + \varepsilon$, with $\varepsilon > 0$. The workers will move to firm R if their contribution to that firm is larger than their contribution to firm F. Then it is necessary that $f^R > f^F$.

Therefore, skilled workers' mobility is most probable to occur when knowledge acquired by the worker has a greater value for firm R than firm F. This is likely to happen when skilled workers participate in innovation projects that are "new to the market" of reference. In these cases, while before the project implementation (period t) the value of the knowledge potentially acquired by C workers is the same for both R and F firms, after the project is implemented $(t + 1)$ the value of this knowledge could be much higher for the R firm. Under the simplifying assumption that firm F is capable to codify the knowledge produced during the innovation process and fully embed it in its production function, the costs of losing C workers would be related only to the potential increased skills acquired by these workers during the process. On the other hand, the benefit of hiring C workers would be related not only to their increased skills, but also to the value (at least part of it) of the knowledge produced during the innovation process.

Assuming that the innovation projects supported by the program are new and relevant to the market, and at least partially codifiable by the innovative firms, C workers would have a strong incentive to move and R firms would have stronger incentives to hire than F firms to retain them.

If this were the case, we would see a quite high mobility of C workers from F firms to R firms. However, some constraints could reduce such mobility. First, if a relevant portion of the knowledge produced by the innovation is non-codifiable (tacit) and remains embedded in C workers, firm F's incentive to retain them would be higher (the value of f^F would be large). Second, the more specific the knowledge is to F firms, the less value it may have for R firms (the value of f^R would be low). Third, if there are mobility costs, the difference in the value of the knowledge acquired by C workers for R and F firms should be higher than these costs. Third, our simplified framework assumes no asymmetric information about the value of the knowledge between F firms, R firms and C workers. In reality, C workers have all the incentives to disclose the value of the knowledge to R firms as much as possible, but also to overstate such value if they can. If the knowledge is generated by highly innovative projects, asymmetries of information about the value of such knowledge are indeed likely to occur. Finally, the model also assumes that there are no negative feedback on the F firms related to the movement of its skilled workers to the R firms. This assumption is much less likely to hold when the F and R firms compete in a highly concentrated market. In an extreme scenario, one firm F and one firm R may be the only providers of a certain product in a specific market. Unless they are already engaged in some collusive behaviors, any increase in efficiency for R would have negative feedback for F. In this case, one could expect a much stronger incentive for F firms to retain their skilled workers and a lower mobility of workers.

Based on this framework, we can test four hypotheses based on the estimation of four key set of parameters. The set of parameters are given by:

A: The effect of the innovation program on the performance of supported firms. This parameter is crucial because it provides evidence on whether relevant productive knowledge has been generated because of the program and, therefore, whether an exogenous knowledge shock −for the firms that did not participate in the program− actually occurred.[9] Obviously, without this effect it is not sensible to look for knowledge diffusion.

B: The effect on the wages of the skilled workers who stay in the F firms after the project has been implemented. This parameter provides evidence on the value for the F firm of the skilled worker after the innovation was implemented.

C: The effect on the wages of skilled workers who moved from firms supported by FONTAR after the project has been implemented. This parameter shows evidence on whether the knowledge acquired through the participation in a FONTAR supported project has some recognizable market value.

D: The effect on the performance of firms that hire skilled workers from firms supported by FONTAR (R firms) after the implementation of the innovation project. This parameter confirms whether the productive value of the knowledge acquired through the participation in the FONTAR program is actually applicable and beneficial to other firms.[10]

The hypotheses about the knowledge generation and diffusion from the innovation program are as follows: (Table 1)

Hypothesis 1: New relevant and at least partially codifiable productive knowledge is diffused through labor mobility. This hypothesis would be confirmed by positive and significant values for the parameters A, C and D. The magnitude of the parameters in D may signal either decay in knowledge transmission (small effects) or some sort of learning by replication (large effects).

[9]Previous studies provide evidence on the validity of this hypothesis. In fact, Hall and Maffioli (2008) summarized the evidence on the effectiveness of several innovation programs similar to FONTAR. The evidence shows that firms participating in programs such as the FONTAR are able to make investments in knowledge that would not be undertaken in the absence of the program. In addition, they show that these types of programs have shown significant effects on firms' investment in R&D, adoption of new products and processes, and eventually firms' performance. All this indicates that beneficiary firms are actually able to create new "productive" knowledge.

[10]Maliranta, Mohnen, and Rouvinen (2009) find that hiring workers previously in R&D to one's non-R&D activities improves productivity and profitability. They interpret this as a transmission of knowledge that can be readily copied and implemented without much additional R&D effort. Similarly, Stoyanov and Zubanov (2012) find that firms that hired skilled workers increased their productivity.

Table 1: Hypotheses

Hypothesis	Value of the parameters
Hypothesis 1	A>0, C>0, D>0
	Small D implies decay in knowledge transmission.
	Large D implies learning by replication.
Hypothesis 2	A>0, C>0, D=0
	D=0 is total decay in knowledge transmission.
Hypothesis 3	A>0, C=0, D=0
	If B>0 the knowledge generated is non-codifiable.
	If B=0 the knowledge is too specific that has no market value.
Hypothesis 4	A>0, and B>0, C=0, D=0 if high concentration.
	A>0, C>0, D>0 if low concentration (in this case D=0 is also possible if there is complete decay as in hypothesis 2)

Hypothesis 2: New relevant knowledge is produced but not diffused, because it is hardly replicable. This hypothesis would be confirmed if the parameters in A and C are positive and significant but the parameters in D are not different from zero. In this case, the knowledge is generated and other firms are willing to pay for it. However, the knowledge does not produce the expected results in other firms.

Hypothesis 3: New relevant knowledge is produced but not diffused, because either non-codifiable or extremely specific. This hypothesis would be confirmed by a strong positive and significant value for parameter A. To distinguish if the lack of knowledge diffusion is due to non-codifiability or the specificity of the knowledge one can look at the magnitude of the parameter in B. In fact, a strong increase in the wage of the skilled workers who did not move after the project implementation may signal an extra effort to retain these workers and, therefore, an important tacit component of the knowledge produced by the innovation. On the other hand, if there is no increase in their wages, this reflects the low value for the market of the knowledge generated in F firms.

Hypothesis 4: New relevant knowledge is produced and diffused only if the innovator does not prevent the diffusion to retain market power. This hypothesis would be confirmed by a strong positive and significant effect for parameter A and zero values of the parameters C and D in sectors with high concentration of firms. In these sectors, high values for B that reflect the willingness of the innovator to retain the workers are expected. In sectors with low concentration of firms, we expect high A and positive C and non-negative D (zero D would imply total decay of knowledge transfer as in hypothesis 2).

2.2 The source for knowledge creation: The FONTAR program

The Argentinian Technological Fund (Fondo Tecnológico Argentino, FONTAR) was created in 1995 and it has been one of the pillars of Argentina's innovation policy. Although the program has evolved and expanded its set of instruments, it has maintained its main focus on providing financial support to innovation projects through two main instruments: (i) reimbursable funding, though targeted credit for innovation, and (ii) non-reimbursable funding, through matching grants and tax credit.[11]

The provision of public funding −either in the form of grants or in the form of targeted credit− aimed at easing market failures that severely constrain innovation and technology adoption projects (Hall and Lerner, 2010). First, the estimation of the risk-adjusted return of innovation and tech-

[11] FONTAR tax credits are non-automatic and project based.

nology adoption investments requires specific technical expertise and a complete understanding of the market of reference −often not yet existing. This clearly implies asymmetries of information between potential investors and innovators that can only be partially remedied with high assessment costs by the investor. Programs such as FONTAR are designed to bear these assessment costs through the establishment and funding of review processes of the technical and commercial viability of the proposed investments. In this sense, the program not only operates as a sort of public venture capitalist, whose returns are the economic return of the investment, but also provides valuable signals to the financial markets on the technical and commercial sustainability of the investment.

Second, the main and most valuable outcomes of innovation projects are intangible and difficult to fully appropriate. These features make the market relationship between investors and innovators even more complicated. In fact, because most of the value of the investment is embedded in knowledge that may spill over to competitors, innovators may be reluctant to share critical information about the design and development of their projects with investors, worsening the asymmetric information problems. In addition, the intangible nature of the innovation outcomes makes it extremely difficult to use these outcomes as collateral, often leading to very high risk premium for investors.

Third, innovation projects are riskier than physical investment projects. For this reason, external investors systematically require higher risk premium for the financing of innovation activities than ordinary investment. Although this is not a market failure per se, public funding targeted to these kinds of projects also aims at increasing their risk-adjusted return for both innovators and potential external investors.

Although these justifications generally apply to the entire program, the justification of each line of funding can be slightly differentiated. In fact, while the whole set of justifications clearly apply to the non-reimbursable instruments, which specifically target R&D projects with higher risks and intangible outcomes, the second and third justifications seem weaker in the case of the reimbursable instruments, which target projects aimed at the adoption of existing knowledge embedded in tangible assets and whose potential returns have already been demonstrated by earlier adopters. In this latter case, the policy intervention substantially solves a problem of asymmetry of information due to the degree of specificity that most likely goes beyond the assessment capacity of the private financial sector.

Programs such as FONTAR clearly aim at increasing firms' investment in innovation and R&D activities (innovation−input outcomes). Although the link between the provision of public funding and investment in innovation seems quite direct, effectiveness at this level still depends on the program's capacity to avoid crowding out effects −where public funding displace or substitute private spending− and to generate multiplier effects −where public funding leverages additional private resources. Participant firms are then expected to translate this increased effort into outputs that reveal the successful realization of the innovation activities,[12] and finally, into better economic performance within the firm and for the economy that provided the fiscal resources.

There is strong evidence showing that FONTAR has been effective in increasing knowledge and innovation within the firms participating in the program. Binelli and Maffioli (2007) found a significant multiplier effect of the program on private investment in R&D. Chudnovsky, López, Rossi, and Ubfal (2006) complemented and reinforced these findings by providing evidence that FONTAR matching-grant lines do not crowd out private investment in R&D (or, in another way, add on the existing private investment in R&D).

Two criteria used in the selection of FONTAR projects were particularly important for our

[12]For this purpose, various innovation-output indicators have been developed, including the number of patents and trademarks registered, the value of sales of new products, and dichotomous indicators on adoption of new processes and products. In terms of economic performance, measures of firm productivity and growth have been increasingly adopted to assess the long-term effectiveness of innovation programs.

study. First, in order to gain the FONTAR support, clear preference was given to those projects that aim at introducing innovations that are at least new to the firm's market of reference. Second, the program also assessed the capability of the firm to perform the innovation with special attention to the presence of skilled employees. While the first criterion ensured that projects had value not only for the firms applying for the support but also for other firms in the same market of reference, the second criterion ensured that participant firms had advanced human capital able to carry out the innovation project in a timely manner to meet the program requirements.

The other key characteristic of the FONTAR program for the identification of the spillover effects is that the knowledge created from the program is exogenous for those firms that did not participate in the program. Therefore, it provides us with an exogenous source of variation that helps to avoid the reflection problem posed by Manski (1993).

2.3 Labor mobility as a source of knowledge diffusion

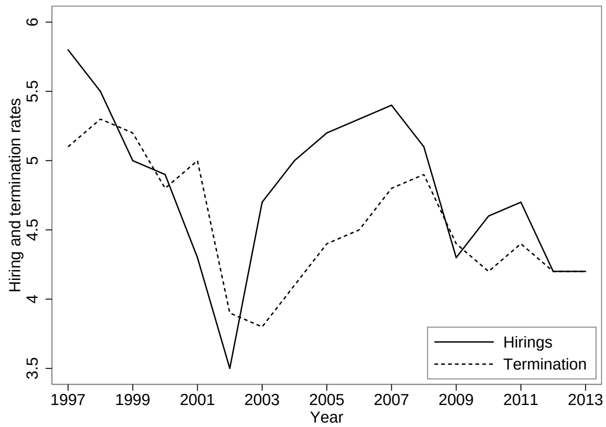
Given that an important part of the knowledge that is created by the innovation program is captured by employees, the most important source of knowledge diffusion in our case is labor mobility. To identify knowledge spillovers through this mobility, we need information both at the firm and employee level. Here is where the employer-employee structure of our data becomes extremely valuable. In fact, it allows us to define precise employment transition matrices and, consequently, to identify those firms that may have benefited from the program indirectly by hiring specialized workers exposed to the knowledge created thanks to the program (receiving firms).

In practice, the identification of receiving firms involves the following steps: (i) identification of participants of the innovation program (FONTAR firms hereafter); (ii) definition of what is a firm-firm relationship that may involve spillover effects; and, (iii) identification of the receiving firms on the basis of this rule. Therefore, we first identify in our dataset the firms that benefited directly from the FONTAR program using the unique tax identification code (CUIT) of each firm. This is a straightforward process which implies merging FONTAR administrative records with the Observatory of Employment and Firms Dynamics (OEDE) dataset.

The definition of firm-firm relationships that involve spillover effects is more challenging. Having already restricted the nature of the relationship to mobility of workers, we then need to define if we want to consider all possible transitions of workers or if some restrictions are needed. In particular, because the FONTAR supports the generation of rather specific and complex knowledge, we cannot simply assume all human resources in the FONTAR firms were exposed or able to absorb this knowledge.

Between 1997 and 2013 labor mobility was considerably high, involving around ten percent of total employment in Argentina every month. This implies that approximately five percent of employees left their current positions and five percent filled them (Figure 1). One of the main factors behind this high labor mobility is the short period of time new workers stay in the firm. In fact, close to 40 percent of new workers left the firm during the first quarter and close to 60 percent during the first year.

Figure 1: Dynamics of private sector employment.
Average of monthly rates, 1997-2013



Source: OEDE.

Because of the high labor mobility, we apply two restrictions for the identification of the workers who may cause knowledge diffusion and therefore spillovers. First, they need to have been exposed to the new knowledge generated in the FONTAR firm long enough to have learned something valuable. For this purpose, we restrict our analysis to the mobility of workers who were employed in a FONTAR firm for at least two years after the firm received the program support. Second, these knowledge carriers need to be able to absorb relatively complex knowledge. Thus, we restrict our analysis to the transfers of the most skilled labor force. Indeed, the mobility of skilled labor has often been identified as one of the most important vehicles through which both formalized and tacit knowledge flow throughout a productive system.[13] Because the only measure of skill in our database is the salary, we focus on the mobility of workers on the top quartile of the salary distribution of the firm of origin.

Summing up, we define receiving firms as those firms that: (i) never participated in FONTAR; and (ii) hired skilled employees (top quartile in the firm wage distribution) that worked in a FONTAR firm for at least two years after the firm of origin received the program support. These criteria allow us to significantly reduce the number of transitions we consider as relevant for potential knowledge spillovers.

Table 2 summarizes the outflows of workers from the firms that received FONTAR support between 1998 and 2006. Around 330,000 workers had been somehow exposed to the FONTAR intervention during this period of time. As we have mentioned above, the overall mobility of this labor force is very high: around 40 percent of these workers eventually moved to a different firm. However, when we restrict the analysis to skilled workers considering a minimum duration of employment in a FONTAR beneficiary firm as defined above, the mobility drops considerably. Only 2.5 percent of total FONTAR workers generated spillovers through knowledge diffusion. These workers created 4,065 receiving firms.

[13] Following Arrow (1962)'s lead, it is frequently suggested that labor mobility is among the key transmission mechanisms of knowledge spillovers (Geroski, 1995; Stephan, 1996; Maliranta, Mohnen, and Rouvinen, 2009).

Table 2: The mobility of workers in FONTAR firms

	Years in a FONTAR firm							
	< 2	2 to 4	4 to 6	6 to 8	8 to 10	10 to 12	> 12	Total
FONTAR firms (856 firms)								
Stay in the firm	54,111	25,473	23,327	18,512	10,798	9,234	56,163	197,618
Move to other firms	79,691	19,399	10,885	6,704	4,282	3,118	8,105	132,184
Total	133,802	44,872	34,212	25,216	15,080	12,352	64,268	329,802
Knowledge carriers	-	2,099	1,302	1,080	800	657	1,371	7,309
Receiving firms	-	1,120	722	625	456	344	798	4,065

3 Data and descriptive statistics

3.1 Data

We combine data from three sources. First, we use social security data with the population of formal firms and all their formally employed workers in Argentina. This data source is an employer-employee panel dataset by firm, worker and year between 1997 and 2013. Second, we match this database with a panel dataset on exports by firm and year between 1998 and 2013. Third, we combine the former two data sources with the administrative records of the FONTAR program.

The employer-employee dataset was constructed by OEDE at the Ministry of Labor, Employment, and Social Security in Argentina.[14] This database includes data from administrative records of two public entities: the National Administration of Social Security (ANSES), and the General Customs Bureau (DGA) of the Federal Administration of Taxes (AFIP). These sources were produced by different organizations, in different moments of time, and with different objectives. This heterogeneity demanded an important work of consolidation of the data. The dataset includes all the firms declaring employment in Argentina after 1997. It covers the primary, manufacturing, and services sectors, and has firm level information about age, location, industry, type of society, whether a firm is multinational, number of employees, average wages, and value of exports, and employee level information about wage, age, gender, and starting and ending date of labor relations. The administrative records of the FONTAR program provide information about the firms that received support between 1998 and 2006 (see A for details).

The fact that we have an employer-employee dataset with whole population of employers and employees is particularly relevant to our study because we can track the mobility of workers between firms.

3.2 Measuring firms' performance

The main advantage of our dataset is that it contains information of every employer and employee in Argentina in the period 1998-2013. Its main limitation, on the other hand, is that it does not contain information about sales and capital and therefore it is not possible to measure firms' productivity. To overcome this limitation we use a series of variables as proxies for productivity.

First, there is a vast literature about the selection hypothesis through which only more productive firms survive (see, for example, Syverson, 2011). Therefore, the survival probability provide us with a proxy for productivity.

[14] Given the confidentiality of the data, the estimations were conducted following the Ministry of Labor, Employment, and Social Security's microdata policy, which implies working under the supervision of its staff and with blinded access to sensible information.

Second, another selection mechanism occurs in the international market; in this case, only more productive firms can enter the export market (See, for example, Bernard, Eaton, Jensen, and Kortum, 2003; Bernard and Jensen, 2004). Furthermore, if only more productive firms can export and there is a reallocation of resources from less productive firms to more productive ones (Melitz, 2003), one can also expect an increase in employment in more productive firms. Because of these reasons, we expect the probability of exporting (extensive margin), the volume of exports (intensive margin), and employment to be proxies for the productivity of the firms.

Finally, we also compute impact on wages as a proxy for improved labor productivity. We use the variation in wages at the worker level to explore whether the knowledge carriers (or skilled workers who stay) enjoyed a wage premium paid by the receiving firms (FONTAR firms).[15] In particular, the change in the average wage paid by each firm can be decomposed into the change in the average due to changes in the wage paid to the workers that continue in the firm from one period to the other, and the change in the average due to hiring/firing workers. These terms allow us to identify two important sources of wage variation at the firm level. While the first one is more related to changes in productivity, the second one is related to changes in the skill composition of the firm. Both terms are relevant in our study. First, given that we are studying spillovers driven from an innovation program, we expect productivity gains caused by innovation. Second, given that the source of spillovers is knowledge diffusion through the mobility of skilled workers, it is possible to expect changes in the skill composition. Let the average wage firm i pays to workers in period t be $W_{it} = \sum_{j=1}^{N_{it}} \frac{1}{N_{it}} w_{jt}$, where w_{jt} is the wage of worker j in period t, and N_{it} the number of workers in firm i in period t. The change in the average wage of each firm i can be decomposed using a similar decomposition of the one used to study the change in aggregate productivity (see, for example, Baily, Hulten, and Campbell, 1992; Foster, Haltiwanger, and Krizan, 2001; Foster, Haltiwanger, and Syverson, 2008). The average wage of firms' decomposition is given by:

$$\begin{aligned} \Delta W_{it} &= \sum_{j \in C} s_{jt-1} \Delta w_{jt} + \sum_{j \in C} \Delta s_{jt} (w_{jt-1} - W_{it-1}) + \sum_{j \in C} \Delta s_{jt} \Delta w_{jt} + \\ &+ \sum_{j \in N} s_{jt} (w_{jt} - W_{it-1}) - \sum_{j \in X} s_{jt-1} (w_{jt-1} - W_{it-1}) \end{aligned} \tag{5}$$

where s_{jt} is the weight of worker i in the average wage and is equal for all the workers in the firm, i.e. $s_{jt} = \frac{1}{N_{it}}$. The sets C, N, and X represent the set of continuing, entering, and exiting workers, respectively. This decomposition has five terms that embody the contributions of various components to the average wage of the firm. The first three terms measure the change in the average wage paid by firm i coming from the workers that continue in the firm. The last two terms measure the change in average wage due to new workers and workers that left the firm. If new workers have wages above average, then the average wage of firm i increases. This could be the case if the firm hires qualified workers. Similarly, if the worker that leaves the firm had a lower wage than the average, the average wage increases. This could be the case if the firm fires less qualified workers. In our estimations, the sum of the first three terms will be used to test the productivity hypothesis while the sum of the last two terms test the skill composition hypothesis.

3.3 Sample and descriptive statistics

Our dataset contains information for 1,571,969 firms between 1998 and 2013 (10,100,174 firm-year observations). Given that the program targeted small and medium-sized firms, we drop firms with

[15] Malchow-Moller, Markusen, and Schjerning (2013) show that workers with foreign firm experience enjoyed a wage premium paid by their new domestic-owned employers.

Table 3: Descriptive statistics, 1998-2013

	Obs.	Mean	SD
A. FONTAR firms			
Number of employees	9,406	72	96
= 1 if export	9,406	0.51	0.5
Value of exports, if exports >0 (thousands of U$S, FOB)	4,820	2,289	6,603
Average monthly wage (LCU)	9,406	2,918	3,002
Productivity term	9,198	519	786
Skill composition term	9,198	35	371
Age	9,406	23	16
= 1 if multinational	9,406	0.03	0.17
= 1 if hire skilled workers	9,406	0.53	0.5
B. Receiving firms			
Number of employees	33,722	103	132
= 1 if export	33,722	0.31	0.46
Value of exports, if exports >0 (thousands of U$S, FOB)	10,372	5,786	44,310
Average monthly wage (LCU)	33,722	3,476	4,437
Productivity term	32,537	604	1353
Skill composition term	32,537	46	690
Age	33,722	20	18
= 1 if multinational	33,722	0.09	0.29
= 1 if hire skilled workers	33,722	0.65	0.48
C. Rest of firms			
Number of employees	1,574,919	25	47
= 1 if export	1,574,919	0.07	0.26
Value of exports, if exports >0 (thousands of U$S, FOB)	110,822	1,779	25,164
Average monthly wage (LCU)	1,574,919	2,195	2,567
Productivity term	1,504,528	403	769
Skill composition term	1,504,528	44	444
Age	1,574,919	17	15
= 1 if multinational	1,574,919	0.01	0.09
= 1 if hire skilled workers	1,574,919	0.33	0.47

less than five employees and more than 500 employees. We also drop firms with less than seven consecutive years in the dataset. We do this because, as it will be explained later, we need several lags to control for firms' past performance and avoid autocorrelation. After these restrictions, the sample shrinks considerably to 128,560 firms and 1,618,047 firm-year observations (see Table B1 in B).[16] Although these sample restrictions requires dropping a high percent of firm-year observations, the reduction helps to construct a much homogeneous sample.

Table 3 shows the basic descriptive statistics (number of observations, mean, and standard deviation) for FONTAR firms, receiving firms and the firms we use to compare them (rest of firms) for the whole period under study.

The analysis reveals that both FONTAR firms and receiving firms are on average larger, older, paid higher wages, and have a higher probability of exporting than the rest of the firms in Argentina. In addition, receiving firms have on average higher outcomes than FONTAR firms, pointing out that knowledge carriers tend to go to larger firms that presumably also have a better performance.

Given that the FONTAR support was not randomly assigned, the pool of non-participant firms is not necessarily comparable to the group of FONTAR firms and hence potential issues of administrative selection and self-selection may arise. This problem is also relevant for the spillover effects. In fact, not only the FONTAR firms may self-select into the program because of characteristics that are related to the outcome of interest, but also receiving firms may be hiring skilled workers because

[16] Most of the reduction in sample size comes from dropping micro firms.

of some characteristics also related to the outcome of interest. In both cases, a simple comparison with the rest of the non-participant firms would lead to biased results. The next section explains the econometric methodology we use to estimate the impact of the FONTAR program on participants, the spillovers effects of knowledge diffusion on receiving firms, and the effect of FONTAR on workers' wage −both if they stay in a FONTAR firm or if they move to other firm.

4 Empirical strategy

Our main objective is to estimate the parameters in Table 1. These parameters measure the effect of FONTAR on participating firms and their workers and the spillover effect generated by the knowledge diffusion between firms. Although these effects are clearly related, for the purpose of our estimates we analyze them as separate and different scenarios or treatments.[17]

The main challenge for identifying these effects is the selection bias coming from the fact that firms decide to participate in FONTAR or to hire skilled workers coming from FONTAR firms and workers decide to stay or move to other firm. These biases can be reduced in a simple regression framework if they are related to observable factors by simply including those factors as control variables in the regressions. In our case, however, some important differences between the groups of firms may also be related to unobservable (or unobserved) factors. To deal with this issue, one may assume that unobserved heterogeneity is constant over time and eliminate these potential sources of bias using a fixed-effects approach. However, many of these unobserved cofounders may be time-varying, such as the entrepreneurial behavior. Indeed, the existence of multiple cohorts of treatments reinforces this idea and points out that firms may change their behavior before applying for program support or hiring a FONTAR skilled worker. That is, the participation into the program or the hiring of the skilled worker depends on past outcomes. In this context, the assumption that the most important omitted variables are time-invariant does not seem plausible.

Our strategy is to take advantage of the panel structure of our data to control for past values of the outcome variable by using a lagged dependent variable (LDV) model. In this case, the identifying assumption is independence of treatment status and potential outcomes conditional on lagged outcome variables and other observable confounders.[18] This assumption implies that after controlling by the lagged dependent variables and other covariates, there is no omitted variables or other sources of endogeneity. This seems a strong assumption. However, as explained below, we control for several lags of the outcome variable and a rich set of interaction terms between year dummies and characteristics that allow us to control for different trends at the individual level and unobservable factors that change over time and affect differently to firms with certain characteristics like industry or location.

To estimate the effect of FONTAR, we use the following equation:

$$Y_{i,s,p,t} = \alpha_{Ft} + \alpha_{Fs,t} + \alpha_{Fp,t} + \alpha_{Fo,t} + \sum_{k=1}^{n} \beta_{Fk} Y_{i,t-k} + \gamma_F F_{i,t-1} + \delta_F X_{i,t} + \varepsilon_{i,s,p,t}, \tag{6}$$

where $Y_{i,s,p,t}$ represents the set of outcomes to be considered for firm i, belonging to industry s, in province p, and year t. α_{Ft} depicts yearly shocks that affect all firms. Regarding the interaction terms, $\alpha_{Fs,t}$ are industry-year effects −i.e. time-specific shocks that affect the outcomes of all firms

[17] Alternatively, the identification could have been approached as a multi-treatment program. A multi-treatment approach could have been a better fit if FONTAR firms had also hired human resources employed in other participant firms, i.e. if some FONTAR firms had received spillover effects from other participant. However, our data shows only few of such cases.

[18] See chapter five in Angrist and Pischke (2009).

in industry $s-$, $\alpha_{Fp,t}$ are province-year effects such as the construction of a freeway, an airport, or implementation of new local policies, and $\alpha_{Fo,t}$ is a vector of two interaction terms that includes type of society-year and multinational-year effects.

$F_{i,t}$ is a binary variable that takes value one the year firm i participates in the program and so thereafter. Therefore, γ_F represents the parameter of interest and it captures the average causal effect of participating in FONTAR on the outcome under consideration. Finally, X_{it} is a vector of time-varying control variables, and $\varepsilon_{i,s,p,t}$ is the usual error term assumed to be uncorrelated with $F_{i,t-1}$ or X_{it}. The sample for this estimation only includes FONTAR firms and firms that did not participate in the program and did not hire FONTAR skilled workers.

Similarly, to estimate the average spillover effect we use the following equation:

$$\begin{aligned} Y_{i,s,p,t} &= \alpha_{Rt} + \alpha_{Rs,t} + \alpha_{Rp,t} + \alpha_{Ro,t} + \sum_{k=1}^{n} \beta_{Rk} Y_{i,t-k} + \\ &\quad \gamma_R R_{i,t-1} + \delta_R X_{i,t} + \varepsilon_{i,s,p,t}, \end{aligned} \tag{7}$$

where $R_{i,t}$ is a binary variable that takes value one after firm i hires a skilled FONTAR worker. Therefore, γ_R measures the average spillover effect. The remaining variables are the same as in equation (6). It is important to note that $X_{i,t}$ includes a binary variable that takes value one after firm i hires a skilled worker. This allows us to separate the effect of hiring skilled workers from the effect of hiring skilled workers with specific knowledge acquired in a FONTAR firm. The set of firms considered in this case are the receiving firms and those firms who did not participate in FONTAR.

The sets of year dummies (α_{Ft} and α_{Rt}) play an important role in our analysis. After a long recession that started in 1998, Argentina suffered a severe crisis in 2001. As a consequence of the crisis, there was a large devaluation of the Argentine Peso and the government declared the default of its sovereign debt. Although in 2002 the GDP contracted by 10.8 percent, in 2003 started a period of growth for Argentina that lasted until 2008. Prices also changed during the recovery and accelerated after 2007. In terms of our study, controlling for these factors is important because the recovery also implied an increase in employment and nominal wages. As long as these factors affected our groups of firms in the same way, the year dummy variables should properly control their influence on employment and wages.

We also relax the assumption of equal effects of the aggregate shocks by controlling for industry-year ($\alpha_{Fs,t}$ and $\alpha_{Rs,t}$) and province-year ($\alpha_{Fp,t}$ and $\alpha_{Rp,t}$) dummies. In this way we allow for time varying shocks that affect firms in different industries or regions in different way. This is important for example for the exchange rate changes that can benefit those firms in tradable sectors and affect those firms in non-tradable using imported inputs. The industry-specific shocks also allow us to deflate wages using an industry-specific price level index. In addition, the province-specific shocks allow us to deflate using province-specific price level indices. The use of province-specific shocks is also important, for example, if the difference in unemployment between provinces lead to a different evolution in wages.

The choice of the lag length for the outcome variable is also important. If the error terms in equations (6) and (7) are auto-correlated, then the estimated coefficients would be inconsistent due to an endogeneity problem. Adding lags of the dependent variable helps reducing the auto-correlation. We then add the minimum number of lags that remove the residual autocorrelation for all outcome variables in order to have a white noise error term.[19] According to our analytical framework, it is also important to estimate the effect at the worker level, both for those workers

[19] As pointed out by Wooldridge (2002), serial correlation is a problem to be dealt with only if the null hypothesis is rejected at the 5% level. However, "In deciding whether serial correlation needs to be addressed, we should remember

who stayed in FONTAR firms, and for those who moved to other firms. To estimate the effect of FONTAR at the worker level for those workers who stayed in a FONTAR firm, we estimate:

$$w_{j,s,p,t} = \alpha_t + \alpha_{s,t} + \alpha_{p,t} + \alpha_{o,t} + \sum_{k=1}^{n} \beta_k w_{j,t-k} + \gamma_S S_{j,t-1} + \delta X_{j,t} + \varepsilon_{j,s,p,t}, \tag{8}$$

where $w_(j,s,p,t)$ is the monthly nominal wage of worker j in period t, X_{jt} is a vector of time-varying control variables at the firm and worker level, and $\varepsilon_{j,s,p,t}$ is the usual error term clustered at the firm level. $S_{j,t-1}$ is a binary variable that takes value one if worker j stayed in the firm for more than two years after the firm participated in FONTAR. To be consistent with the fact that these workers are skilled workers with at least two years of tenure in the firm, our sample only includes workers with these characteristics; i.e. skilled workers with at least two years in the current firm.

Similarly, to estimate the effect on the FONTAR workers who moved to other firms, we estimate

$$w_{j,s,p,t} = \alpha_t + \alpha_{s,t} + \alpha_{p,t} + \alpha_{o,t} + \sum_{k=1}^{n} \beta_k w_{j,t-k} + \gamma_M M_{j,t-1} + \delta X_{j,t} + \varepsilon_{j,s,p,t}. \tag{9}$$

In this case we use the sample of skilled workers (with at least two years in the current firm) who move to non-FONTAR firms. $M_{j,t}$ is a binary variable that takes value one after the FONTAR worker j (knowledge carrier) moves to a non-FONTAR firm. $X_{j,t}$ is a vector of covariates including firms age and age squared, worker's gender, age, age squared, and tenure. Like in the analysis at the firm level, we include year dummies, industry-year, province-year, type of society-year, and multinational-year dummies. Each equation also includes as many lags of the dependent variable as necessary to control for the autocorrelation in the error terms.

In addition to the average effect, we are also interested in estimating how the spillover effect at the worker and firm level evolves over time. For this purpose, we replace the binary treatment variables $(S_{j,t-1}, M_{j,t-1}, R_{j,t-1})$ with a set of binary variables that includes a dummy variable that takes value one the first two years, a dummy variable that takes value one between the third and fifth year, and a dummy variable that takes value one after 5 years (after the worker stays in a FONTAR firm after support, the worker moves to other firm or after the firm receives the knowledge carrier, respectively). Therefore, these new treatment dummies measure the dynamics of the impacts of interest. More specifically, given that our equations control for past values of the outcome variable, the coefficients of these variables capture the additional effect for each post-treatment period included in the analysis.

Finally, given that our analytical framework provides different behavior for the FONTAR and receiving firms depending on the competition in the good market, we also estimate the average effects for different level of competition. For this purpose, we construct a Herfindahl-Hirschman index (HHi) for the relevant market; we assume that market is province-industry specific. Therefore, we construct HHi using firms' labor costs by province-sector and allow time variation to capture changes in the market concentration. Using HHi, we classify markets in two categories: (i) competitive market if HHi<0.01 and (ii) concentrated market if HHi≥ 0.01.[20] The resulting dummy variables are interacted with the treatment variables to analyze the heterogeneity of the impacts of interest by level of competition.

the difference between practical and statistical significance. With a large sample size, it is possible to find serial correlation even though $\hat{\rho}$ is practically small; when $\hat{\rho}$ is close to zero, the usual OLS inference procedures will not be far off" (Wooldridge, 2002, pp. 397).

[20]Traditionally, the HHi is divided in four categories: An HHi<0.01 indicates a highly competitive index, between 0.01 and 0.15 an unconcentrated index, between 0.15 to 0.25 moderate concentration, and above 0.25 high concentration. In order to avoid power problems due to the lower number of observations in higher concentrated markets, we divide the HHi in two main categories. For a full discussion on measures of concentration, see Tirole (1988).

5 Results

5.1 The impact of FONTAR

Previous studies found that the FONTAR increased R&D expenditures of its beneficiaries and improved their innovation profile; both in terms of process and product innovation (Chudnovsky, López, Rossi, and Ubfal, 2006; Binelli and Maffioli, 2007). These studies, however, were not able to estimate the program's long-term effect on performance variables, such as productivity or firms' growth. To reinforce the evidence on the FONTAR additionality, in this sub-section we provide some estimates of such long-run effects.

Table 4 shows our estimation of equation (6) for different outcome variables. We find that the program fostered firms' growth in terms of employment (4.8%), enhanced probability of exporting (3.7pp), and increased the value of exports (9.8%). Consistently, participant firms also increased their probability of surviving in the medium-long run (1.6%).

The program had also a clear positive effect on the average monthly wage paid to employees (0.8%). As shown by the last two columns in Table 4, this wage increase is clearly related to the workers that stay in the firms, confirming the increased productivity hypothesis. In fact, we also find that the wage variation due to the change in the skill composition is statistically non-significant.[21]

These findings confirm that the FONTAR program has effectively induced "additional" efforts to generate and adopt new knowledge which then is reflected in higher growth, exports, and productivity. This finding not only shows that the FONTAR beneficiaries were actually able to create new and relevant productive knowledge, but also confirms that an exogenous knowledge shock −for non-beneficiary firms− actually occurred because of the program.

5.2 The impact on skilled workers who stayed in the firm

Having identified the firm-level effects, we then explore the program effect on the wages on those skilled workers who stayed in the FONTAR beneficiary firms after the project was implemented. In addition to provide further evidence about the productivity gains due to the program, this estimation will also provide a first measure of the change in the perceived value of the skilled workers exposed to the FONTAR projects and, therefore, a first element to approximate the relevance of the knowledge generated by the program.

Table 5 reports regression results for equation (8) using worker−level data. This table compares skilled workers who stayed in the firm for at least two years after the firm participation in FONTAR with skilled workers with at least two years of tenure in non-beneficiary firms. We find (column 1) a 1.4 percent average effect on wages, which almost doubles the effect on wages obtained using firm-level data. This difference is consistent with the hypothesis that skilled workers are the ones acquiring most of the knowledge related to the design and implementation of the innovation projects supported by the program.

In addition to the average effect, we also estimate how the effect evolves over time. We find that the overall effect on wages increases over time, but at a decreasing rate, as shown by the positive but decreasing coefficients of the dummy variables in column 2. Also, we find that this effect on skilled-worker wages reaches its maximum magnitude (3.3%) during the first two years after program support. This short-term effect likely reflects some level of compensation offered to skilled workers for the newly acquired knowledge to prevent them from being hired elsewhere. On the other end, the long-term effects are more likely related to productivity gains.

[21] Given that this pattern in wages variation might be also explained by differences in the age or tenure of workers within firms, we run equation (6) for the last three columns of Table 4 controlling for workers' average age, age square, tenure and tenure squared (Table B3). The results are robust to the additional control variables.

Table 4: Long-term effect of FONTAR on participant firms

Dependent variable:	# of employees (in logs) [1]	1 if exporting [2]	Exports (in logs) [3]	1 if survives [4]	Average wage (in logs) [5]	Productivity hypothesis [6]	Skill composition hypothesis [7]
Average effect on participants	0.048***	0.037***	0.098***	0.016***	0.008***	57.237***	-0.928
	(0.004)	(0.003)	(0.017)	(0.001)	(0.002)	(11.145)	(5.062)
Number of observations	805,495	805,495	34,563	805,495	805,495	805,495	805,495
Number of firms	126,080	126,080	6,150	126,080	126,080	126,080	126,080
R-squared	0.891	0.729	0.839	0.018	0.949	0.337	0.053
Ho: no serial correlation							
rho	0.006	-0.002	0.001	-	0.002	0.011	-0.012
p-value	0.077	0.553	0.932	-	0.561	0.82	0.899

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include six lags of the outcome variable, year, industry-year,province-year, multinational-year, type of society-year dummies, age and age squared, and a dummy variable that takes value one the year after the firm hired skilled workers and so thereafter. (c) Robust standard errors in parentheses. (d) ***, **, * statistically significant at 1%, 5%, and 10%.

Table 5: Effect on skilled workers who stay in FONTAR firm

Dependent variable:	Wage (in logs)		
	[1]	[2]	[3]
Average effect	0.014***		
	(0.003)		
Dynamics of effect			
1st/2nd years		0.033***	
		(0.006)	
3rd/4th/5th years		0.016***	
		(0.005)	
6th/+ years		0.008**	
		(0.004)	
Effect by competition level			
HHi<0.01			0.015
			[0.011]
HHi≥0.01			0.014***
			[0.003]
Number of observations	9,570,703	9,570,703	9,570,703
Number of workers	1,523,211	1,523,211	1,523,211
Number of firms	123,438	123,438	123,438
R-squared	0.934	0.934	0.934
Ho: no serial correlation			
ρ	-0.002	-0.002	-0.002
p-value	0.454	0.451	0.454

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include four lags of the outcome variable,year, industry, province, multinational, and type of society dummies, firm's age and age squared, worker's gender, age, age squared and tenure.(c) HHi is the Herfindahl-Hirschman index. (d) Clustered standard errors at the firm level in parentheses. (e) ***, **, * statistically significant at 1%, 5%, and 10%.

Finally, to further explore the motivations behind this wage increase, we also estimate how the average effect varies with the level of competition. Results show that the effect on wages actually comes from skilled workers operating in concentrated sectors (column 3). This finding confirms the hypothesis that beneficiary firms operating in concentrated sectors have higher incentive to retain those skilled workers who gained knowledge through the exposure to the FONTAR supported projects. That is, in sectors with high concentration beneficiary firms are more willing to invest in retaining their skilled workers to prevent negative feedback that may occur if competitors hire these workers and eventually increase efficiency thanks to the knowledge generated by the FONTAR projects.

5.3 A wage premium for knowledge carriers

What happened with the skilled workers who eventually moved? Did they capture part of the knowledge created by the program? To answer these questions we estimate equation (9) comparing knowledge carriers with other skilled workers who moved from non-beneficiary firms where they worked for at least two years. Table 6 shows that knowledge carriers actually received higher wages than other skilled moving workers, confirming that the knowledge acquired through the participation in the FONTAR project has a recognizable market value. In particular, the estimate on wages is 3.5 (column 1), i.e. 2.5 times higher than that for skilled workers who did not move (1.4). Moreover, in this case the effects are sustained over time (column 2).

When analyzing the heterogeneity of the effects by competition level, one may consider whether the knowledge carrier moves to a firm in the same or different sector. In general, we find that the knowledge carriers that belong to a firm from a competitive sector receive higher wages than those belonging to firms from more concentrated markets (column 3). Movements within the same sector are the most relevant. In fact, in a less concentrated market it is more likely that FONTAR firms allow workers to move by not offering substantial wage increases and therefore workers will find higher wages in other firms. The result on wages reveals a positive and significant effect of 7.9%, while in higher concentrated markets the effect is much smaller and non-significant—this might reflect that FONTAR firms increase the wage to retain these workers and, in consequence, the lower mobility of workers between firms is lower.[22]

5.4 Knowledge spillovers through labor mobility

To identify knowledge spillovers, we estimate equation (7). In this case, we compare firms that hired skilled workers from FONTAR beneficiaries (i.e. the knowledge carriers) with firms that did not. In this estimation, the dummy variable that controls for whether a firm has been hiring skilled workers from any other firms becomes much more relevant.[23] In fact, because the hiring of skilled workers might improve a firm's performance per se, without controlling for this factor we might confound spillovers for improvements due to better matching between worker skills and the firm's needs.

The results in Table 7 show that firms that hired the knowledge carriers actually improved their performance in several dimensions. In particular, receiving firms increased employment (3.7%), probability of exports (1.7pp), value of exports (9.9%), survival probability (0.7%), and the average

[22]As a robustness check we run another specification of equation (9) but controlling for the lagged average wage paid by their employer. This specification takes into account the fact that workers may simply be moving into more productive firms that pay higher wages. Table B4 shows that our results are robust to this additional control.

[23]We do this by including a dummy variable that takes value one the year after the firm hired skilled workers and so thereafter. Although this control variable was also included in the previous estimations, in this case it is clearly more relevant.

Table 6: Effect on knowledge carriers

Dependent variable:	Wage (in logs)		
	[1]	[2]	[3]
Average effect	0.035***		
	(0.008)		
Dynamics of the effect			
1st/2nd years		0.035**	
		(0.015)	
3rd/4th/5th years		0.028***	
		(0.007)	
6th/+ years		0.044***	
		(0.009)	
Effect by competition level and type of movement			
Same sector			
HHi<0.01			0.079***
			(0.027)
HHi≥0.01			0.018
			(0.011)
Different sector			
HHi<0.01			0.050***
			(0.013)
HHi≥0.01			0.035***
			(0.011)
Number of observations	2,628,556	2,628,556	2,628,556
Number of workers	358,626	358,626	358,626
Number of firms	174,413	174,413	174,413
R-squared	0.902	0.902	0.902
Ho: no serial correlation			
ρ	0.002	0.002	0.002
p-value	0.431	0.431	0.431

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include three lags of the outcome variable, year, industry, province, multinational, and type of society dummies, firm's age and age squared, worker's gender, age, age squared and tenure at the firm of origin. (c) HHi is the Herfindahl-Hirschman index. (d) Clustered standard errors at the firm level in parentheses. (e) ***, **,* statistically significant at 1%, 5%, and 10%.

wage they pay to their employees (0.9%), with magnitudes that are in general lower than those obtained by FONTAR firms, but still relevant and statistically significant. From the last two columns of Table 7 we observe that the increase in wages is mostly due to an increase in the wage of workers that were already in the receiving firms rather than the wage of the newly hired skilled workers. This finding reveals that the increase in wages is due to an improvement in productivity, rather than to a change in the skill composition. These results confirm the hypothesis that the knowledge acquired through the exposure to a FONTAR project has a productive value that goes beyond the firm directly supported by the program.[24]

An additional source of identification of the spillover effect is the fact that not every firm hired the same number of knowledge carriers. We then explore how the spillover effects vary according to the share of knowledge carriers to total workers in receiving firms.

Table 8 shows similar results to those in Table 7. However, instead of a dummy variable identifying receiving firms, the main explanatory variable is a continuous variable that measures the ratio between the number of knowledge carriers received with respect to the number of workers at the moment of receiving the knowledge carriers. Therefore, this variable measures how the spillover effects react to changes in the intensity of the knowledge diffusion. As expected, the more knowledge carriers received with respect to the number of workers in the firms, the higher the spillover effect *ceteris paribus*.[25]

Moreover, given that we observe receiving firms each year after they hire the knowledge carrier, we can estimate the way in which the spillover effect takes place in time. Table 9 shows these estimates. They provide us with another robustness check to previous findings. In general, the cumulative spillover is increasing in time for all outcome variables under analysis. Of particular interest is the dynamics of the effects on the productivity and skill composition terms (Figure 2). In the former case, the spillover effect increases over time at a growing rate, as shown by the increasing coefficients of the treatment dummy variables.

[24] As with the direct impact of FONTAR, we run an additional specification for the last three columns of Table 7 controlling for workers' average age, squared age, tenure and squared tenure (Table B5). The findings reinforces the previous effects obtained on the average wage and its decomposition.

[25] In addition to this estimation, we run an alternative specification including two dummies variables instead of the ratio. The first one takes value 1 if the firm hired only one knowledge carrier while the second one takes value 1 if the firm hired two or more, and 0 otherwise. As shown in Table B6 the spillovers effects are higher when hiring more knowledge carriers. This is consistent with the findings in Table 8.

Table 7: Spillover effects

Dependent variable:	# of employees (in logs) [1]	1 if exporting [2]	Exports (in logs) [3]	1 if survives [4]	Average wage (in logs) [5]	Productivity hypothesis [6]	Skill composition hypothesis [7]
Average spillover effect	0.037***	0.017***	0.099***	0.007***	0.009***	111.496***	18.933***
	(0.004)	(0.002)	(0.019)	(0.001)	(0.002)	(14.844)	(6.208)
Number of observations	818,585	818,585	36,596	818,585	818,585	818,585	818,585
Number of firms	127,921	127,921	6,481	127,921	127,921	127,921	127,921
R-squared	0.895	0.732	0.843	0.018	0.949	0.334	0.053
Ho: no serial correlation							
ρ	0.006	-0.002	0.000	-	0.002	0.004	-0.011
p-value	0.067	0.524	0.984	-	0.555	0.929	0.905

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include six lags of the outcome variable, year, industry-year, province-year, multinational-year, type of society-year dummies, age and age squared, and a dummy variable that takes value one the year after the firm hired skilled workers and so thereafter. (c) Robust standard errors in parentheses. (d) ***, **, * statistically significant at 1%, 5%, and 10%.

Table 8: Spillover effects by intensity of the knowledge diffusion

Dependent variable:	# of employees (in logs) [1]	1 if exporting [2]	Exports (in logs) [3]	1 if survives [4]	Average wage (in logs) [5]	Productivity hypothesis [6]	Skill composition hypothesis [7]
# of knowledge carriers /	0.006***	0.003***	0.018***	0.001***	0.001***	19.698***	3.765***
# of employees (in logs)	(0.001)	(0.000)	(0.004)	(0.000)	(0.000)	(2.762)	(1.197)
Number of observations	818,585	818,585	36,596	818,585	818,585	818,585	818,585
Number of firms	127,921	127,921	6,481	127,921	127,921	127,921	127,921
R-squared	0.895	0.732	0.843	0.018	0.949	0.334	0.053
Ho: no serial correlation							
ρ	0.006	-0.002	0	-	0.002	0.004	-0.011
p-value	0.068	0.525	0.983	-	0.555	0.929	0.905

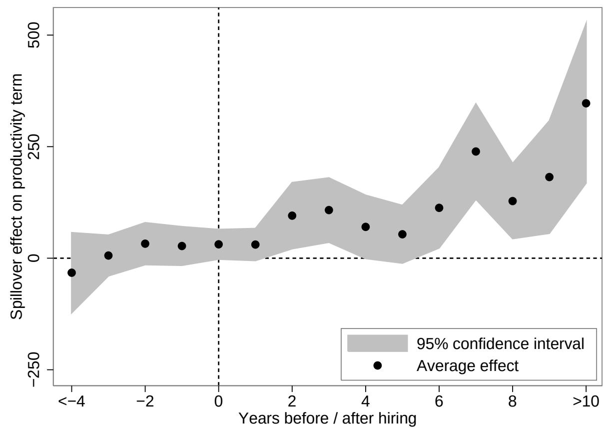
Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include six lags of the outcome variable, year, industry-year, province-year, multinational-year, type of society-year dummies, age and age squared, and a dummy variable that takes value one the year after the firm hired skilled workers and so thereafter. (c) Robust standard errors in parentheses. (d) ***, **, * statistically significant at 1%, 5%, and 10%.

Table 9: The dynamics of the spillover effect

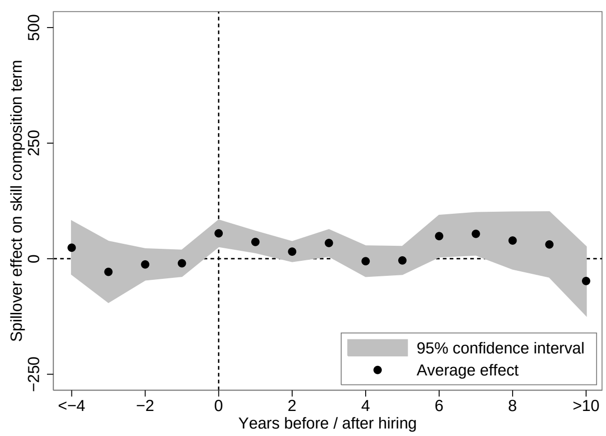
Dependent variable:	# of employees (in logs) [1]	1 if exporting [2]	Exports (in logs) [3]	1 if survives [4]	Average wage (in logs) [5]	Productivity hypothesis [6]	Skill composition hypothesis [7]
1st/2nd years	0.051***	0.021***	0.075**	0.010***	0.006**	67.134***	23.150***
	[0.007]	[0.003]	[0.036]	[0.002]	[0.003]	[21.662]	[8.465]
3rd/4th/5th years	0.032***	0.017***	0.110***	0.007***	0.008***	80.745***	7.51
	[0.006]	[0.003]	[0.028]	[0.002]	[0.003]	[21.213]	[9.067]
6th/+ years	0.029***	0.013***	0.107***	0.005**	0.012***	191.803***	28.811**
	[0.006]	[0.004]	[0.031]	[0.002]	[0.003]	[28.336]	[12.888]
Observations	818,585	818,585	36,596	818,585	818,585	818,585	818,585
Number of firms	127,921	127,921	6,481	127,921	127,921	127,921	127,921
R-squared	0.895	0.732	0.843	0.018	0.949	0.334	0.053
Ho: no serial correlation							
ρ	0.006	-0.002	0.000	-	0.002	0.004	-0.011
p-value	0.068	0.522	0.978	-	0.555	0.929	0.905

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include six lags of the outcome variable, year, industry-year, province-year, multinational-year, type of society-year dummies, age and age squared, and a dummy variable that takes value one the year after the firm hired skilled workers and so thereafter. (c) Robust standard errors in parentheses. (d) ***, **, * statistically significant at 1%, 5%, and 10%.

Figure 2: Dynamics of the spillover effect



(a) Productivity term



(b) Skill composition term

Finally, we can test whether the effect of hiring a knowledge carrier depends on the level of competition of the sector the firm belongs to. Table 10 shows that the effects tend to be higher for receiving firms in competitive markets. Results also reveal that the knowledge generated through the FONTAR projects seems to be general instead of specific to a particular firm or industry. That is, knowledge coming with these new hires is general enough to be applied in different firms and to overcome technical barriers between different industries.

Summarizing, in terms of our analytical framework our results clearly reject hypothesis two and three and provide evidence in favor of hypothesis one. In fact, we find that new relevant productive knowledge is generated and diffused through labor mobility. The positive effects of the FONTAR program on the long-term performance of supported firms ($A > 0$) confirms that an exogenous knowledge shock for non-participants actually occurred. We then find that this new productive knowledge is applicable and beneficial to non-participant firms that access to it through labor mobility, as shown by their improved long-term performance ($D > 0$). Finally, our results also support hypothesis four as the knowledge spillovers are higher in industries with a low concentration

Table 10: The spillover effect by competition level

Dependent variable:	# of employees (in logs) (1)	1 if exporting (2)	Exports (in logs) (3)	1 if survives (4)	Average wage (in logs) (5)	Productivity hypothesis (6)	Skill composition hypothesis (7)
Same sector							
HHi<0.01	0.044***	0.018***	0.072	0.006*	0.014***	74.546***	45.505***
	[0.013]	[0.006]	[0.107]	[0.003]	[0.005]	[23.756]	[16.117]
HHi≥=0.01	0.041***	0.015***	0.114***	0.004	0.003	58.396***	23.341**
	[0.008]	[0.004]	[0.029]	[0.003]	[0.003]	[20.835]	[10.349]
Different sector							
HHi<0.01	0.052***	0.017***	0.160***	0.012***	0.007	28.876	44.865**
	[0.011]	[0.006]	[0.053]	[0.003]	[0.005]	[26.520]	[19.040]
HHi≥0.01	0.031***	0.018***	0.082***	0.006***	0.011***	149.322***	12.25
	[0.005]	[0.003]	[0.025]	[0.002]	[0.002]	[21.911]	[8.344]
Observations	818,585	818,585	36,596	818,585	818,585	818,585	818,585
Number of firms	127,921	127,921	6,481	127,921	127,921	127,921	127,921
R-squared	0.895	0.732	0.843	0.019	0.949	0.335	0.054
Ho: no serial correlation							
ρ	0.006	-0.002	0.000	-	0.002	0.004	-0.011
p-value	0.066	0.524	0.99	-	0.54	0.929	0.905

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include six lags of the outcome variable, year, industry-year, province-year, multinational-year, type of society-year dummies, age and age squared, and a dummy variable that takes value one the year after the firm hired skilled workers and so thereafter. (c) HHi is the Herfindahl-Hirschman index. (d) Robust standard errors in parentheses. (e) ***, **, * statistically significant at 1%, 5%, and 10%.

of firms. At the worker level, our findings show that a wage premium is paid to skilled workers exposed to the program either by participant (to retain, $B > 0$) or non-participant firms (to acquire, $C > 0$) depending on the level of concentration of the industry of reference. These findings further confirm the hypothesis that the productive knowledge generated through the innovation program has recognizable market value and is more extensively diffused in less concentrated industries.

6 Conclusions

The goal of this paper was to study the effects of knowledge spillovers on firms' performance and workers' wages. For this purpose, we used the participation in an innovation support program as an exogenous shock to the knowledge stock of non-participant firms. We pinpointed the knowledge diffusion process by tracking the mobility of skilled workers among firms based on a 16-years employer-employee panel dataset. We introduced a simple analytical framework that outlines a set of hypothesis to be tested in our empirical analysis and to guide the interpretation of our findings.

To test these hypotheses, we organized our empirical analysis at two levels: firm and worker level effects. At the firm level, we estimated both the effects of receiving skilled workers that previously worked in a firm that participated in the innovation program −knowledge carriers− and the effects of receiving the FONTAR support on different measures of firm performance. At the worker level, we estimated the effect on wages of staying at the participating firm and the effect of moving to non-participant firms.

We found strong and robust evidence in favor of positive knowledge spillovers through labor mobility. In fact, we found that firms that hired knowledge carriers improved their performance after hiring them. They increased their size in terms of number of employees, their probability of exporting, the value of their exports, their survival probability, and the average wages they pay. Consistent with the hypothesis that effects are caused by newly acquired productive knowledge, we also found that these effects were driven by an improvement in firm-level productivity.

At the worker level, our results are also consistent with the existence of knowledge spillovers. In particular, our findings show that skilled workers exposed to the FONTAR program received a wage premium, whether they stayed at the beneficiary firm or they moved to another firm. These results confirm that skilled workers acquired valuable productive knowledge and that firms were willing to pay to either retain or acquire such knowledge depending on the level of competition of their market of reference. More specifically, in relatively less concentrated markets non-beneficiary firms were willing to pay a wage premium to acquire such workers higher than the wage premium beneficiary firms would pay to retain them. However, when the market was concentrated, beneficiary firms were willing to pay a higher premium than non-beneficiaries to prevent these workers from being hired by a competitor who could have threatened their market position.

In synthesis, our findings clearly confirm the hypothesis that valuable productive knowledge was generated through the FONTAR program, that this knowledge spilled over through labor mobility, and that knowledge diffusion is more intense in less concentrated industries.

The policy implications of our work are straightforward. First, our findings strongly support the most important justification of innovation policy, i.e. the incomplete appropriation of benefits by the investors in innovation. Therefore, the use of transfers —in the form or subsidies and matching grants—is certainly an advisable approach to promote knowledge creation and increase productivity. Second, because externalities in the form of spillover effects are often not precisely considered in ex-ante cost-benefit analyses of this kind of instrument, the decision on the magnitude of such interventions could be downward biased and lead to design programs that are not consistent with their potential social return, most likely undersized and underfunded.

Our dataset is both an advantage and a limitation. On the one hand, it allows us to track the mobility of every worker in Argentina and therefore to identify an important source of knowledge diffusion. On the other hand, it does not contain data about occupations and it does not allow us to measure firms' productivity. Having detailed data on occupations would have allowed us to better define knowledge carriers, for example, those workers more involved in the innovation project. Similarly, having productivity information would have allowed us to directly measure the impact on firms' productivity.

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A Source of data

Source I: Administrative records of the National Administration of Social Security (ANSES) from the Observatory of Employment and Entrepreneurial Dynamics (OEDE) at the Ministry of Labor, Employment, and Social Security in Argentina. Period: 1997-2013.

Firm-level data:

- Employment: number of formal employees in October.
- Average wage: ratio of the sum of monthly wages of formal employees to the number of formal employees in October.
- Age.
- Location: province.
- Industry: 2-digit SIC sector level.
- Type of society: Individual society, SA, SRL, other commercial societies, other association forms.
- Multinational: whether the firm is multinational or not.

Employee-level data:

- Wage: monthly wage in October.
- Age.
- Gender.
- Tenure.

Source II: Administrative records of the General Customs Bureau (DGA) from the Observatory of Employment and Entrepreneurial Dynamics (OEDE) at the Ministry of Labor, Employment, and Social Security in Argentina. Period: 1998-2013.

- Exports: value of exports in US$ fob.

Source III: Administrative records of the FONTAR program.

- FONTAR: whether the firm receives support or not.
- Year of support.

B Additional Tables

Table B1: Number of firms and observations before-after sample restriction

Period 1998-2013	Population	Sample after constraints			
		FONTAR firms	Receiving firms	Rest of firms	Total
Number of firms	1,571,969	639	2,480	125,441	128,560
Observations	10,100,174	9,406	33,722	1,574,919	1,618,047

Notes: The criteria for dropping firms were: i) firms with less than five employees or more than 500 employees; and, ii) firms with less than seven consecutive years in the dataset.

Table B2: Number of FONTAR and receiving firms by cohort

Year	FONTAR firms	Receiving firms
1998	44	-
1999	59	-
2000	42	50
2001	72	67
2002	31	71
2003	79	145
2004	189	226
2005	98	217
2006	25	224
2007	-	310
2008	-	300
2009	-	267
2010	-	273
2011	-	330
Total	639	2,480

Table B3: Long-term effect of FONTAR on participant firms. Robustness Check

Dependent variable:	Average wage (in logs) [5]	Productivity hypothesis [6]	Skill composition hypothesis [7]
Average effect on participants	0.009***	55.33***	0.802
	(0.002)	(10.915)	(5.054)
Number of observations	805,021	805,021	805,021
Number of firms	126,080	126,080	126,080
R-squared	0.95	0.34	0.06
Ho: no serial correlation			
ρ	0.002	0.012	-0.013
p-value	0.494	0.800	0.895

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include six lags of the outcome variable, year, industry-year, province-year, multinational-year, type of society-year dummies, age and age squared, a dummy variable that takes value one the year after the firm hired skilled workers and so thereafter, workers' average age, age square, tenure and tenure squared. (c) Robust standard errors in parentheses. (d) ***, **, * statistically significant at 1%, 5%, and 10%.

Table B4: Effect on knowledge carriers. Robustness check

Dependent variable:	Wage (in logs)		
	[1]	[2]	[3]
Average effect	0.032***		
	(0.007)		
Dynamics of the effect			
1st/2nd years		0.031**	
		(0.014)	
3rd/4th/5th years		0.025***	
		(0.007)	
6th/+ years		0.044***	
		(0.008)	
Effect by competition level and type of movement			
Same sector			
HHi<0.01			0.077***
			(0.025)
HHi≥0.01			0.019*
			(0.012)
Different sector			
HHi<0.01			0.048***
			(0.013)
HHi≥0.01			0.031***
			(0.010)
Number of observations	2,628,556	2,628,556	2,628,556
Number of workers	358,626	358,626	358,626
Number of firms	174,413	174,413	174,413
R-squared	0.90	0.90	0.90
Ho: no serial correlation			
ρ	0.003	0.003	0.003
p-value	0.137	0.137	0.137

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include three lags of the outcome variable, year, industry, province, multinational, and type of society dummies, firm's age and age squared, worker's gender, age, age squared, tenure at the firm of origin and the lagged average wage of employers. (c) HHi is the Herfindahl-Hirschman index. (d) Clustered standard errors at the firm level in parentheses. (e) ***, **, * statistically significant at 1%, 5%, and 10%.

Table B5: Spillover effects. Robustness check

Dependent variable:	Average wage (in logs) [5]	Productivity hypothesis [6]	Skill composition hypothesis [7]
Average spillover effect	0.011***	127.285***	9.982*
	(0.002)	(15.415)	(6.019)
Number of observations	818,103	818,103	818,103
Number of firms	127,921	127,921	127,921
R-squared	0.95	0.34	0.06
Ho: no serial correlation			
ρ	0.002	0.005	-0.012
p-value	0.491	0.920	0.901

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include six lags of the outcome variable, year, industry-year, province-year, multinational-year, type of society-year dummies, age and age squared, a dummy variable that takes value one the year after the firm hired skilled workers and so thereafter, workers' average age, squared age, tenure and squared tenure. (c) Robust standard errors in parentheses. (d) ***, **, * statistically significant at 1%, 5%, and 10%.

Table B6: Spillover effects by intensity of the knowledge diffusion. Robustness check

Dependent variable:	# of employees (in logs) [1]	1 if exporting [2]	Exports (in logs) [3]	1 if survives [4]	Average wage (in logs) [5]	Productivity hypothesis [6]	Skill composition hypothesis [7]
1 if the firm hires only	0.025***	0.013***	0.081***	0.005***	0.008***	78.831***	15.874**
one knowledge carrier	[0.004]	[0.002]	[0.023]	[0.001]	[0.002]	[14.875]	[6.407]
1 if the firm hires two	0.072***	0.029***	0.135***	0.011***	0.011***	199.091***	36.310**
o more knowledge carriers	[0.007]	[0.004]	[0.031]	[0.002]	[0.003]	[32.677]	[14.400]
Number of observations	818,585	818,585	36,596	818,585	818,585	818,585	818,585
Number of firms	127,921	127,921	6,481	127,921	127,921	127,921	127,921
R-squared	0.895	0.732	0.843	0.019	0.949	0.335	0.054
Ho: no serial correlation							
ρ	0.006	-0.002	0.000	-	0.002	0.004	-0.011
p-value	0.065	0.524	0.983	-	0.541	0.929	0.905

Notes: (a) OLS estimates of lagged dependent variable model. (b) All regressions include six lags of the outcome variable, year, industry-year, province-year, multinational-year, type of society-year dummies, age and age squared, and a dummy variable that takes value one the year after the firm hired skilled workers and so thereafter. (c) Robust standard errors in parentheses. (d) ***, **, * statistically significant at 1%, 5%, and 10%.