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Worker Mobility and Knowledge Diffusion in Local Labor Markets

By
Michel Serafinelli

A dissertation submitted in partial satisfaction of the
requirements for the degree of

Doctor of Philosophy

in

Economics

in the

Graduate Division

of the

University of California, Berkeley
Committee in charge:

Professor David Card, Co-Chair
Professor Enrico Moretti, Co-Chair

Professor Patrick Kline
Professor Steven Raphael

Fall 2013

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Abstract

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A prominent feature of the economic landscape in the most developed countries is the tendency for firms to locate near other firms producing similar products or services. In the United States, for example, biopharmaceutical firms are clustered in New York and Chicago and a sizeable share of the elevator and escalator industry is concentrated in the area around Bloomington, Indiana. In addition, the growth and diffusion of multinational corporations has led to the recent appearance of important industrial clusters in several emerging economies. Firms that originally agglomerated in Silicon Valley and Detroit now have subsidiaries clustered in Bangalore and Slovakia (Alfaro and Chen, 2010).

Researchers have long speculated that firms in industrial concentrations may benefit from agglomeration economies, and a growing body of work has been devoted to studying the importance of these economies. Despite the difficulties involved in estimating agglomeration effects, a consensus has emerged from the literature that significant productivity advantages of agglomeration exist for many industries (Rosenthal and Strange, 2003; Henderson, 2003; Ellison, Glaeser and Kerr, 2010; Greenstone, Hornbeck and Moretti, 2010; Combes et al., 2012). Localized knowledge spillovers are a common explanation for the productivity advantages of agglomeration. Nevertheless, as pointed out by Combes and Duranton (2006), if information can easily flow out of firms, the question of why the effects of spillovers are localized must be clarified.

This dissertation directly examines the role of labor mobility as a mechanism for the transfer of efficiency-enhancing knowledge and eval-

uates the extent to which labor mobility can explain the productivity advantages of firms located near other highly productive firms. The underlying idea is that knowledge is embedded in workers and diffuses when workers move between firms. The strong localized aspect of knowledge spillovers discussed in the agglomeration literature may thus arise from the propensity of workers to change jobs within the same local labor market.

In order to empirically assess the importance of labor-market based knowledge spillovers, I use matched employer-employee data from the centre and north-east of Italy (mainly Veneto, but also Emilia Romagna and Tuscany). While the issues analyzed in this study are of general interest, the case of this region is important because it is an economic area where networks of specialized small and medium-sized firms, frequently organized in districts, have been effective in promoting and adapting to technological change during the last three decades. This so called "Third Italy" region has received a good deal of attention by researchers, in the United States as well as in Europe.

In chapter 1, titled "Labor Mobility as a Mechanism for Knowledge Transfer", I present direct evidence on the role of firm-to-firm labor mobility in enhancing the productivity of firms located near highly productive firms. More specifically, I identify a set of high-wage firms (HWF) and show they are more productive than other firms. I then show that hiring a worker with HWF experience increases the productivity of other (non-HWF) firms.

In chapter 2, titled "Worker flows and Agglomeration Advantages", I relate the findings In Chapter 1 to the existing evidence on the productivity advantages of agglomeration. Simulation results indicate that worker flows explain 10-15 percent of the productivity gains experienced by other firms when HWFs in the same industry are added to a local labor market.

In chapter 3, titled "Mobility of Inventors and Innovation", my coauthor Sabrina Di Addario and I investigate the relationship between worker flows and innovative activity. We use a unique dataset that matches administrative employer-employee records to patent data and focus on labor market mobility of inventors. While inventors are not

the only workers that may transfer relevant information from one firm to another, they undoubtedly have a large potential to do so. Our preliminary results show that the number of workers who have applied for a patent while working at a previous firm is positively and statistically significantly related to patenting activity of the current firm's other employees.

To Pamela and Serena

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Acknowledgments

"Beaucoup de nouveaux moralistes dans notre ville allaient alors, disant que rien ne servait à rien et qu'il fallait se mettre à genoux. Et Tarrou, et Rieux, et leurs amis pouvaient répondre ceci ou cela, mais la conclusion était toujours ce qu'ils savaient : il fallait lutter de telle ou telle façon et ne pas se mettre à genoux» (Albert Camus, La Peste, 1947)

I am incredibly grateful to the co-chairs of my committee, David Card and Enrico Moretti. Their work has been a constant source of inspiration, and their insightful comments and encouragement have had a very important impact on this study. I also greatly benefited from the sharp and constructive criticism of Pat Kline, both in and out the Labor Therapy Session room. Special thanks are also due to Steven Raphael and Bronwyn Hall for their enthusiasm and guidance.

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Serena: The months we spent together in the Bay Area are unforgettable. After you left, you were still present in my life. Your brother always thinks of you. You perfectly represent the spirit of our family that is so important to me.

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Michel

Chapter 1

Labor Mobility as a Mechanism for Knowledge Transfer

1.1 Introduction

In this Chapter I present direct evidence on the role of firm-to-firm labor mobility in enhancing the productivity of firms located near highly productive firms, using a unique dataset from the Veneto region of Italy that combines Social Security earnings records and detailed financial information for firms. I begin by presenting a simple conceptual framework where some firms are more productive because they have some superior knowledge. Employees at these firms passively acquire some proportion of the firm's internal knowledge. For simplicity, I refer to these as "knowledgeable" workers. Other firms can gain access to the superior knowledge by hiring these workers. Empirically, I identify potential high-productivity firms as those that pay a relatively high firm-specific wage premium.[1] I show that these high-wage-firms (HWFs) have higher labor productivity, higher value added, and higher capital (in particular intangible capital) per worker, suggesting the presence of a firm-specific productivity advantage and thus a point of origin for the transfer of knowledge. Next, I evaluate the extent to which non HWFs benefit from hiring knowl-

[1] This is consistent with many recent models of frictional labor markets (e.g., Christensen et al., 2005), in which higher-productivity firms pay higher wages for equivalent workers.

edgeable workers by studying the effect on productivity associated with hiring workers with recent experience at HWFs.

Productivity shocks that are correlated with the propensity to hire knowledgeable workers may give rise to an upward bias in the impact of knowledgeable workers. In order to address this potential endogeneity issue, I use control function methods from the recent productivity literature (Olley and Pakes, 1996; Levinsohn and Petrin, 2003). Another potential threat to identification is the fact that I do not observe labor quality. In particular, since the good firms pay a relatively high firm-specific wage premium, workers who separate from a good firm may be of lower quality. I refer to this potential adverse selection problem as "lemons bias" (Gibbons and Katz, 1991). Lemons bias will tend to work against the finding of a positive effect of knowledgeable workers. In order to address this issue, I obtain a proxy for worker ability and I weight the number of workers in my OLS regression using the average ability to obtain effective labor input.

I conclude that hiring a worker with HWF experience significantly increases the productivity of other (non HWF) firms. A non HWF hiring at the mean gains 0.14-0.28 percent in productivity compared to an observationally identical firm that hired no knowledgeable workers. This gain is equivalent to moving 0.2-0.5 centiles up the productivity distribution for the median firm. The productivity effect of knowledgeable workers is not associated with recently hired workers in general; I do not find a similar productivity effect for recently hired workers without experience at good firms.

The number of knowledgeable workers may also be correlated with productivity shocks happening in the future if workers can foresee them and apply for jobs in firms with better growth prospects. To deal with this threat to identification, I adapt the control function methods to proxy for future productivity shocks. As an alternative approach, I instrument for the number of knowledgeable workers in a non HWF with the number of local good firms in the same industry that downsized in the previous period. Indeed, following a downsizing event at a HWF, it is more likely that a knowledgeable worker applies for job at local non HWFs because s/he is unemployed and does not want to relocate far

away, and not because some particular non HWF offers better prospects than the HWF at which the worker is employed. This instrumental variable (IV) strategy also further guards against the possibility of lemons bias: the larger the number of workers laid off from HWFs, the lower, arguably, the extent of selection. The IV estimates return an economically and statistically significant effect of recruiting knowledgeable workers on non HWF productivity, with the point estimate larger than the OLS. While in principle this is consistent with the idea that the OLS coefficient is biased downward (lemons bias), in practice the IV standard errors are large and prevent me from drawing definitive conclusions.

1.2 Conceptual Framework and Empirical Strategy

Assume there exists a finite number of locations, each constituting a separate local labor market. To fix ideas, assume that these labor markets are completely segmented with workers being immobile between them. There exists a finite collection $\mathcal{J} = \{\mathcal{J}_0, \mathcal{J}_1\}$ of firms consisting of the set $\mathcal{J}_1$ *good* firms, which are more productive because they have some superior knowledge and set $\mathcal{J}_0$ other firms which have no access to the superior knowledge. The superior knowledge is exogenously given and could include information about export markets, physical capital, process innovations, new managerial techniques, new organizational forms and intermediate inputs. Workers employed by good firms acquire some proportion of the firms' internal knowledge. For simplicity, I assume that this acquisition of internal knowledge takes place immediately after the workers join the good firm. Workers are *knowledgeable* if they have knowledge of the relevant information and *unknowledgeable* otherwise. All workers employed by good firms, then, are knowledgeable. Additionally, some proportion of this knowledge can be *transferred* to a $j \in \mathcal{J}_0$ firm if the workers switch employers.[2] The production function of firm

[2] I assume that this type of knowledge cannot all be patented and that exclusive labor contracts are not available.

$j \in \mathcal{J}_0$ is

$$Y_j = F(L_j, K_j, M_j) = A_j[(\overline{\theta}_j L_j)^{\alpha} K_j^{\gamma} M_j^{\lambda}]^{\delta} \tag{1.1}$$

where $L = H + N$, i.e. the sum of knowledgeable workers (H, who moved at some point from a good firm to a non-good firm) and unknowledgeable workers (N); $\overline{\theta}$ is the quality of the workforce, K is total capital inputs, M is material inputs, and $\delta < 1$ represent an element of diminishing return to scale, or to "span of control" in the managerial technology (Lucas, 1978).[3] I allow for knowledge transfer by by letting workers' productivity depend on H:

$$A_j = D_j e^{\beta_H H_j} \tag{1.2}$$

I obtain the regression equation that forms the basis of my empirical analysis, by combining equation (1.1) and (1.2) and taking logs:

$$\ln(Y_{jslt}) = \beta_L \ln(\overline{\theta}_{jslt} L_{jslt}) + \beta_K \ln(K_{jslt}) + \beta_M \ln(M_{jslt}) + \beta_H H_{jslt} + \beta_0 + \zeta_{jslt} \tag{1.3}$$

The dependent variable is the real value of total firm production, s denotes industry, l denotes locality and t denotes year.[4] The variable of interest, H is constructed from head counts in the matched employer-employee data. The term $\ln(D_j)$ is decomposed into two elements, β_0 and ζ_{jslt}. The constant β_0 denotes mean efficiency across all firms in $\mathcal{J}_0$ that is due to factors others than H. The time-variant ζ_{jslt} represents deviations from this mean efficiency level and captures (a) unobserved factors affecting firm output, (b) measurement error in inputs and output, and (c) random noise. Estimating the effect of recruiting a knowledgeable worker on a firm's productivity is difficult in the presence of unobservable contemporaneous productivity shocks, unobserved labor quality and unobservable future productivity shocks. I turn now to describing what type of biases these unobservables may introduce and how I deal with them in the empirical work.

[3] This is in line with the large presence, that I document below, of small and medium size firms in the non-HWF sample.

[4] Notice that $\beta_L = \delta\alpha, \beta_K = \delta\gamma, \beta_M = \delta\lambda$.

1.2.1 Productivity shocks at time t

Express ζ_{jslt} , the deviations from mean firm efficiency not resulting from knowledge transfer, as

$$\zeta_{jslt} = \omega^*_{jslt} + \nu_{jslt} = \omega_{jslt} + \mu_{st} + \varpi_{lt} + \nu_{jslt} \tag{1.4}$$

which specifies that ζ_{jslt} contains measurement error ν_{jslt} and a productivity component ω^*_{jslt} (TFP) known to the firm but unobserved by the econometrician. The productivity component can be further divided into a firm-specific term, a term common to all firms in a given industry (μ_{st}) and a term common to all firms in a given locality (ϖ_{lt}). Equation (1.3) now becomes:

$$\begin{aligned} \ln(Y_{jslt}) &= \beta_0 + \beta_L \ln(\overline{\theta}_{jslt} L_{jslt}) + \beta_K \ln(K_{jslt}) + \beta_M \ln(M_{jslt}) & (1.5) \\ &+ \beta_H H_{jslt} + \mu_{st} + \varpi_{lt} + \omega_{jslt} + \upsilon_{jslt} & (1.6) \end{aligned}$$

One major difficulty in estimating β_H in Equation (1.5) is that non HWFs may decide on their choice of H based on the realized firm-specific productivity shock (ω_{jslt}) unknown to the researcher. When employing OLS to estimate Equation (1.5) without accounting for the existence of ω_{jslt}, the bias induced by endogeneity between H and ω_{jslt} is likely positive (positive productivity shocks translate into higher probability to hire from HWFs), implying that the coefficient estimate will be biased upward ($\widehat{\beta_H} > \beta_H$).

I employ the productivity literature's techniques to control for the endogeneity of inputs in order to assess the relevance of this issue in my setting. In particular, I apply the Olley and Pakes (1996, henceforth OP) and the Levinsohn and Petrin (2003, henceforth LP) approaches. OP construct an explicit model for the firm's optimization problem in order to obtain their production function estimator. Essentially, the authors address the issue of endogeneity of inputs by inverting the investment function to back out—and thus control for—productivity. Building on OP, LP suggest the use of intermediate input demand in place of investment demand as a proxy for unobserved productivity. The results are shown in Section 1.4. See Eberhardt and Helmers (2010) for an in-depth

discussion of these 'structural' estimators.

1.2.2 Unobserved Worker Quality

Another potential threat to identification is the fact that I do not observe labor quality. In particular, since the good firms pay a relatively high firm-specific wage premium, workers who separate from a good firm may be of lower quality. This lemons bias may work against the finding of a positive effect of knowledgeable workers. In order to address this issue, I obtain a proxy for worker ability and I weight the number of workers in my OLS regression using the average ability to obtain effective labor input. Specifically, I weight the total number of workers L by firm j's average worker ability level $\overline{\theta}_{jslt} = \frac{1}{L_{jslt}} \sum_{i=1}^{L_{jslt}} \theta_i$, to obtain effective labor input. $\overline{\theta}_{jslt}$ is time-varying at the firm level, given that the number and composition of workers change. In order to obtain the individual θ_i, I procure estimates of worker fixed effects from wage equations where both firm and worker effects can be identified. Section 1.2.5 describes this estimation in detail.

The IV strategy based on the events of downsizing at good firms (described in Section 1.2.4) further guards against the possibility of lemons bias: the larger the number of workers laid off from HWFs, the lower, arguably, the extent of selection.

1.2.3 Productivity shocks at time t+1

The number of knowledgeable workers may be correlated with productivity shocks happening in the future if workers can foresee them and apply for jobs at firms with better growth prospects. If such firms prefer to hire workers from good firms, these workers will have a higher probability of being chosen. To the extent that preferring workers from good firms can be explained through knowledge transfer from these firms, a positive correlation between H and the receiving firm's productivity shocks in $t+1$ does suggest a role for labor mobility as a channel for knowledge transfer, even though it will overestimate its importance (Stoyanov and

Zubanov, 2012).

In an effort to proxy for productivity shocks in $t+1$ that may be anticipated by the workers, I add polynomial functions of capital and investment and of capital and materials in both t and $t+1$. This is in the spirit of the OP and LP approaches and assumes that hiring firms are also able to anticipate their productivity shocks and adjust their inputs accordingly. As an alternative approach to deal with this issue, I adopt an IV strategy that I now describe.

1.2.4 Using the number of downsizing firms as IV

In Section 1.4.1 I present estimates where I instrument for the number of knowledgeable workers in a non HWF with the number of *local* good firms in the *same 5-digit industry* that downsized in the previous period. The IV strategy is an alternative approach to deal with the strategic mobility issue discussed in the previous section. Indeed following a downsizing event at a HWF, it is more likely that a knowledgeable worker applies for job at local non HWFs because s/he is unemployed and does not want to relocate far away, and not because some particular non HWFs offer better prospects than the HWF at which the worker is employed. Put differently, in the scenario captured by the IV approach, the strategic mobility explanation is less likely to play a major role.

One can think of two main reasons why good firms may downsize in a particular year. First, good firms may get a bad draw from the distribution of product-market conditions. Even though an inherent productivity advantage partly insulates the good firms from output shocks, sufficiently large shocks will pierce this insulation and induce the good firm to layoff workers. Alternatively, good firms may downsize in a particular year due to offshoring.

The basic intuition behind the IV approach is to consider moves from workers whose former employer downsized due to demand shocks or offshoring. While the timing of these moves is arguably exogenous, these workers may still decide which new employer to join among the set of non-HWFs. However, in small labor markets and specialized industries, workers may have a limited set of alternatives (Tecu, 2012).

The choice of the instrument is based on the notion that geographic

proximity plays an important role in determining worker mobility. In January 2012, I visited several Veneto firms and interviewed employees about the history of their enterprises and their current operations. I also conducted phone interviews with officials of employers' associations and chambers of commerce. My anecdotal evidence supports the idea that distance acts as a barrier for job mobility.[5] In Section 2.4.1 I further discuss the role of geographic proximity.

In the presence of product demand shocks or offshoring, using the number of downsizing firms as an instrument is invalid if it cannot be excluded from the causal model of interest (Equation 1.3). The identifying assumption of my IV strategy is therefore that the number of downsizing good firms is correlated with the causal variable of interest, H, but uncorrelated with any other unobserved determinants of productivity.

1.2.5 Identification of Good Firms

Empirically, I identify potential high-productivity firms as high-wage firms (HWFs), i.e. those that pay a relatively high firm-specific wage premium. This is consistent with many recent models of frictional labor markets (e.g., Christensen et al., 2005), in which higher-productivity firms pay higher wages for equivalent workers. As I shall show below using balance sheet data, HWFs have significant higher output per worker and value added per worker than other firms in my sample.

There are three reasons why I define the good firms as HWFs and detect them using Social Security data rather than define the good firms directly as the highly productive ones and detect them using balance sheet data. First, the availability of worker-level Social Security data allows the introduction of measured individual characteristics and worker effects, something impossible to capture with firm level data from balance sheets. Second, Social Security data are available for a longer period of time than the balance sheets, and therefore increase the precision of the

[5] In a phone interview, Federico Callegari of the Treviso Chamber of Commerce, reasoned out the role of geographic proximity: "I think distance matters a lot for workers' job mobility. When losing their job, workers tend to look for another job with a commuting time of maximum 20-30 minutes. Why? Because they want to go home during the lunch break!"

categorization of firms into good and non-good groups. Third, since Social Security records are administrative data, measurement error is lower than in balance sheets.

Following Abowd, Kramarz and Margolis (1999, henceforth AKM), I specify a loglinear statistical model of wages as follows:

$$w_{ijt} = X'_{it}\beta + \theta_i + \psi_j + v_t + \varepsilon_{ijt} \tag{1.7}$$

where the dependent variable, the log of the average daily wage earned by worker i in firm j in year t, is expressed as a function of individual heterogeneity, firm heterogeneity, and measured time-varying characteristics.[6] The assumptions for the statistical residual ε_{ijt} are (a) $E[\varepsilon_{ijt}|i,j,t,x] = 0$, (b) $Var[\varepsilon_{ijt}|i,j,t,x] < \infty$ and (c) orthogonality to all other effects in the model. The presence of labor mobility in matched worker-firm data sets enables the identification of worker and firm effects.[7] I identify good firms as those whose estimated firm fixed effects fall within the top third of all estimated firm effects. Section 1.3.1 reports descriptive results as well as more details on the estimation procedure.

1.3 Data and Descriptive Statistics

The data set is for Veneto, an administrative region in the Northeast of Italy with a population of around 5 million people (8 percent of the country's total). Section 2.2.2 provide a detailed decsription of the regional economy and explains why Veneto is an interesting laboratory to study the topic of labor-market based knowledge spillovers.

My data set pools three sources of information: individual earnings

[6] The vector X'_{it} includes tenure, tenure squared, age, age squared, a dummy variable for manager and white collar status, and interaction terms between gender and other individual characteristics.

[7] The identification relies on the assumption that mobility is exogenous to the included regressors. Bias in the estimated firm effects arises when errors predict specific firm-to-firm transitions. Card, Heining and Kline (2012) conduct a series of checks for patterns of endogenous mobility that could lead to systematic bias in AKM's additive worker and firm effects model. The authors find little evidence of such biases in German data.

records, firm balance sheets, and information on local labor markets (LLMs).[8] The earnings records come from the Veneto Workers History (VWH) dataset. The VWH has data on all private sector personnel in the Veneto region over the period 1975-2001. Specifically, it contains register-based information for virtually any job lasting at least one day. A complete employment history has been reconstructed for each worker.

Balance sheets starting from 1995 were obtained from AIDA (Analisi Informatizzata delle Aziende), a database circulated by Bureau Van Dijk containing official records of all incorporated nonfinancial Italian firms with annual revenues of at least 500,000 Euros. AIDA's balance sheets include firms' location, revenues, total wage bill, the book value of capital (broken into subgroups), value added, number of employees, value of materials and industry code. I use firm identifiers to match job-year observations for workers aged 16-64 in the VWH with firm financial data in AIDA for the period 1995-2001. Further details on the match and data restrictions I make, as well as descriptive information are provided in section 1.7.1. In particular Table 1.2 summarizes the sample of non HWFs used in the main firm-level analysis – equation (1.3).

Information on LLMs is obtained from the National Institute of Statistics (ISTAT). The LLMs are territorial groupings of municipalities characterized by a certain degree of working-day commuting by the resident population. In 1991 the 518 municipalities or *comuni* in Veneto are divided into 51 LLMs.

1.3.1 AKM Estimation and Descriptive Results

The method in Abowd, Creecy and Kramarz (2002) identifies separate groups of workers and firms that are connected via labor mobility in matched employer-employee data. When a group of workers and firms is connected, the group contains all persons who ever worked for any firm within the group and all firms at which any of the persons were ever employed. I run the grouping algorithm separately using VWH data from 1987 to 2000 for firms that could be matched in AIDA. I then use

[8] The first two sources, combined for the period 1995-2001, have been used in the study on rent-sharing, hold-up and wages by Card, Devicienti and Maida (2010).

the created group variable to choose the largest group as a sample for my fixed-effects estimation - Equation (1.7). Details on sample restrictions and descriptive information are provided in section 1.7.1. Figure 1.1 shows the distribution of estimated firm effects.

I identify HWFs as those firms whose firm effects rank in the top third of the sample.

For labor mobility to generate productivity benefits of agglomeration, a firm-specific advantage should be observed at good firms that could be the basis for knowledge transfer to other firms in the region. Therefore, once I have categorized firms into HWF and non HWF groups, I estimate:

$$\ln O_{jst} = \beta_0 + \beta_1 HWF_{js} + \mu_s + v_t + e_{jst} \tag{1.8}$$

where the dummy HWF takes the value of 1 if firm j is classified as high-wage and O_{jst} represents different firm-level outcomes. Table 1.1 shows the results of estimating Equation (1.8).

In the Veneto manufacturing sector clear differences between HWFs and non HWFs emerge in labor productivity (measured as output per worker, Column 1), value added per worker (Column 2) and capital per worker (Column 3), including both tangible capital (Column 4) and, most remarkably, intangible fixed assets (Column 5). This evidence is important for establishing the potential for knowledge transfer in the region. Since labor productivity is on average 15 percent higher in HWFs, and intangible capital per worker (intellectual property, accumulated research and development investments and goodwill) is 27 percent larger, we can also think of HWFs as high-productivity firms, or high-intangible-capital firms. Table 1.3 illustrates that, in contrast to firm characteristics, workforce characteristics of HWFs and non HWFs are not very different. The shares of white collar workers and managers are 1.8 and 0.3 percentage points higher, respectively, in HWFs; the share of female workers is 3.1 percentage points lower. No difference emerges in the share of workers younger than 30 or older than 45.

1.3.2 The Extent of Labor Mobility

For labor mobility to be a mechanism for transfer of knowledge, we must observe some workers moving from HWFs to other firms. On average, between 1995 and 2001, 4.3 percent of non HWFs in a given year employ workers with HWF experience. Overall, 1187 workers switch from HWFs to non HWFs during my sample period.[9]

It is important to observe that these numbers do not imply that in a typical year 4.3 percent of Veneto firms are potentially affected by knowledge transfer. Recall that I only consider flows from firms in the top third of estimated firm fixed effects to firms in the bottom third. As a result, these numbers should be interpreted as implying that in a typical year about 4.3 percent of the firms in the bottom third of the distribution employ at least one worker with experience at a firm in the top third. There obviously exists significant labor mobility within the two groups that may also serve as a channel of knowledge transfer. To illustrate, one can intuitively imagine that a worker moving from a firm in the 1st percentile of the distribution to a firm in the 19th percentile may bring efficiency-enhancing knowledge to his or her new job[10], and the same can be imagined for a worker moving from a firm in the 21st percentile to a firm in the 99th percentile. However I focus solely on flows between the two groups.

It is also important to note that the percentage of firms that employ workers with HWF experience varies with the threshold that I impose on the distribution. For instance, if I define HWFs as firms with fixed effects in the top half of the overall distribution, 8.4 percent of non HWFs em-

[9] 787 are blue collar workers, 331 are white collar workers, 46 are managers and 23 are apprentices.

[10] Despite potential lawsuits due to violations of non-compete covenants and trade secret law, one frequently observes top firms poaching employees from competitors in an effort to acquire some of their internal knowledge. This poaching is sometimes so intense that companies may cut deals to refrain from competing for employees. In December 2010, the U.S. Justice Department settled an antitrust suit with Lucasfilm over a "no solicitation" agreement with rival Pixar. In September of the same year, the Justice Department had settled another suit over similar agreements involving Adobe Systems, Apple, Google, Intel, Intuit and Pixar (The New York Times, January 2, 2011).

ploy workers with HWF experience, compared with 4.3 percent if HWFs are defined by falling in the top third of the fixed-effects distribution.

Below I show estimates of the extent to which non HWFs benefit from hiring workers from HWFs by entering an annual firm-level measure (H) of the number of workers with experience at HWFs into a production function. Since only a small subest of non HWFs in a given year employ workers with HWF experience, the mean value of H workers across the sample of non HWFs is small (0.071). The maximum value is 7. Notice that the mean number of employees at non HWFs is 48, and the median is 33.

As regards to individual characteristics of the movers in my sample, in all years movers from HWFs are significantly more likely to be young and male than non HWFs workers without experience at good firms. In most years, these movers are also significantly more likely to be white-collar workers and managers. Table 1.4 and 1.5 give descriptive statistics in the most recent year (2001) for movers from good firms to non HWFs and non HWFs workers without experience at good firms.

1.4 Evidence on Worker Flows and Productivity

In this section I present the main results from regression analysis in my study. Specifically, I evaluate the extent to which non HWFs benefit from hiring workers from HWFs. Estimation of Equation (1.3) is performed over the period for which balance sheet data are available (1995-2001). Details on sample restrictions and descriptive statistics for the variables used in the regression analysis are provided in section 1.7.1. Table 1.6 shows the estimation results. I cluster standard errors at the firm level. Coefficients associated with the H measure in Table 1.6 represent semi-elasticities because my variable of interest is not in logarithms. This choice for the baseline specification, which directly follows from Equation (1.2), is founded on the fact that H takes on the value 0 for the majority of observations. Thus, any possible transformation of the H measure could possibly affect the associated estimated parameters. In

any case, in Section 1.4.2 I show results using different functional forms.

Column 1 reports estimate from the baseline OLS specification: the coefficient on H_{jst} is positive (0.039) and significant.[11] Column 2 and 3 of Table 1.6 employ the productivity literature's techniques to control for the endogeneity of inputs. H_{jst} is treated as a freely variable input. Column 2 reports results using the OP estimator: the coefficient for H_{jst} is positive (0.037) and significant.[12] Column 3 reports the results for LP estimator: the coefficient for H_{jst} is positive (0.020) and significant; it is lower than the OLS estimate, confirming the theoretical and empirical results on variable inputs discussed in LP.[13]

Although the estimate of the coefficients for H_{jst} in the OP and LP specification are smaller than the baseline estimate, none of the specifications is qualitatively inconsistent with the empirical finding that labor mobility works as a channel of knowledge transfer. The point estimates suggest that the average effect of recruiting a knowledgeable worker on a non HWF's productivity is an increase of between 2 and 3.9 percent. This seems like a very large effect. However, I discuss in section 1.3.2, the mean number of knowledgeable workers is 0.071 and as many as 95.7 percent of non HWFs in a given year do not employ any worker of this type. Hiring one worker of this type therefore implies a large change for most firms in our data (Notice also that non-HWFs are quite small: the

[11] All inputs are positive and statistically significant, and the labor coefficient is an expected 71% of the summed coefficients for labor and capital. The overall production function has mild decreasing returns to scale, with a 1 percent increase in all inputs leading to a 0.9 percent increase in output.

[12] I use the opreg Stata routine developed by Yasar, Raciborski and Poi (2008). I do not observe investment, and hence derived a proxy variable in t as the difference between the reported book value of capital at time $t+1$ and its value in t. The way I constructed the proxy variable somehow exacerbates the measurement error problems typically associated with the proxy variable approach. In addition, augmenting my specification with this proxy variable reduces my sample size substantially, as (a) 3871 firm-year observations are lost when I take the difference in reported book values and (b) the OP approach requires positive values for the proxy variable, eliminating an additional 7174 firm-year observations. (The estimation routine will truncate firms' non-positive proxy variable observations because the monotonicity condition necessary to invert the investment function, and hence back out productivity, does not hold for these observations.)

[13] I use the *levpet* Stata routine developed by Petrin, Poi and Levinsohn (2004).

median number of employees at non HWFs is 33).

As a further illustration of Table 1.6's estimates, given the mean value of H (0.07) and its slope coefficient in Column 1, $\widehat{\beta_H}$ =0.039, a non-HWF hiring at the mean H gains $0.039 \cdot 0.07 = 0.28$ percent in productivity compared to an observationally identical firm that hired no-one. This gain is equivalent to moving 0.5 centiles up the productivity distribution for the median firm. If one uses the LP estimate instead of the OLS, the gain is equal to 0.14 percent (0.2 centiles up in the distribution).

In an effort to proxy for productivity shocks in t+1 that may be anticipated by the workers (recall the discussion in Section 1.2.3), in Column 4 and 5 I add polynomial functions of capital and investments or capital and materials in t and $t+1$. These estimates also suggest that non HWFs benefit from knowledgeable workers by experiencing increased productivity.[14] In Section 1.4.1 I show results from the IV strategy, an alternative approach to deal with the strategic mobility issue that may arise as a result of the presence of unobservable shocks in $t+1$.

Next, I address the questions of whether the knowledge embedded in workers is general enough to be applied in different industries: Column 6 of Table 1.6 differentiates between workers with HWF experience moving within the same two-digit industry and workers moving between industries. The coefficient of knowledgeable workers moving within industry is highly significant and positive (0.072). The coefficient of knowledgeable workers moving between industries is significant and positive but smaller (0.024). The difference in the two coefficients is significant at conventional levels.

Overall, the main empirical result in this Section is that labor mobility from HWFs to other firms in the region works as a mechanism for the transfer of efficiency-enhancing knowledge. Hiring within the same industry brings more relevant new knowledge than that which can be acquired from workers previously employed outside.

section 1.4.2 investigates the robustness of these findings to different specifications and explores potential alternative explanations of the esti-

[14] That said, most of the components in the polynomial approximations are statistically significant, implying that these extra terms contribute in explaining the variation in productivity among firms. Notice the drop in observations due to the fact that we are using the leads of inputs (polynomials in $t+1$).

mated productivity effects. In particular, I investigate the role of the selection of movers based on observable characteristics and unobserved firm heterogeneity. I also evaluate the role of functional form assumptions, and I explore the importance of time-varying unobservables correlated with the number of recent hires.

1.4.1 IV Estimates

In this section I instrument for the number of knowledgeable workers using the lagged number of good local firms in the same 5-digit industry that downsized in the previous period. This exercise is motivated by the possibility of strategic mobility and lemons bias that I discussed above. The exclusion restriction is violated and $\widehat{\beta_H}^{IV}$ is biased upward if there are localized unobservable industry shocks that lead good firms to downsize and *positively* affect productivity at non HWFs. Below, I further discuss the validity of the IV strategy.

Turning to the details of the instrument, a downsizing firm must see an employment reduction larger than 3 percent *compared to the previous year's level*. The division of good firms into downsizing and non-downsizing firms according to this criterion is less sensible for small firms. Accordingly, I impose the additional condition that the decrease in the labor force is greater than or equal to three individuals. The instrumental variable is summarized in Table 1.7.

Table 1.8 shows the results from the IV estimation of Equation (1.3). Standard errors are clustered at the level of the LLM.

The F test of excluded instruments in Column 1 gives a statistic of 23.1[15]. The estimated coefficient of H is large: $\widehat{\beta_H}^{IV} = 0.268$. However, the standard error is also large (0.154). The coefficient is significant at the 10 percent level.

A concern for the validity of the exclusion restriction arises from the observation that the dependent variable in my econometric model is the

[15] The coefficient of the number of downsizing firm in the first-stage regression is equal to .017 (standard error is 0.003). A one standard deviation increase in the instrumental variable is associated with an increase in H of 0.02.

value of output.[16] Unobserved shifts in local demand from HWFs to non HWFs might simultaneously lead to (a) higher output prices for non HWFs, (b) downsizing by HWFs and (c) hiring of HWF employees by non HWFs. The LLM-year effects control for local demand shocks, but localized unobservable *industry* shocks may still play a role. Consequently, in principle, it is possible that $\widehat{\beta_H}^{IV} > 0$ reflects higher output prices, rather than higher productivity due to knowledge transfer. I do not expect this to be a major factor in my context; manufacturing firms in my sample generally produce goods traded outside the LLM.[17] To further explore this possibility in Column 2 I add a dummy taking value one if the industry produces goods that are not widely traded outside the LLM.[18] The results in Column 2 are very similar to those in Column 1.

Even when the level of tradability is controlled for, product demand effects might still be relevant and $\widehat{\beta_H}^{IV}$ might therefore be biased if an industry is strongly localized. In such a scenario the negative shock to the local HWF may lead to increased demand for the non HWF firm j even though the HWF and the non HWF produce a tradable good. This is because, since most of the firms producing that particular good in Italy are in the same Veneto LLM, the non HWF may experience an increase in demand, and hence in price, after the negative shock to a local HWF that is a direct competitor on the national market. To address this concern, I construct an index of industry localization as follows $r_s = (Italian\ Firms\ in\ s)/(Veneto\ Firms\ in\ s)$. Industries with low r have a relatively small number of firms outside the Veneto area. In Column 3 I enter r_s as additional regressor: the F test gives a slightly larger statistic (24.4) and $\widehat{\beta_H}^{IV}$ is estimated slightly more precisely (standard error is 0.145). The point estimate is very similar.

[16] The theoretically correct dependent variable in a productivity study is the *quantity* of output, but, due to data limitations, this study (and virtually all the empirical literature on productivity) uses price multiplied by quantity.

[17] Imagine the extreme case of a non-HWF that produces a nationally traded good in a perfectly competitive industry. Its output prices would not increase disproportionately if the LLM experienced an increased demand for its good.

[18] See Appendix 1.7.2 for details.

Finally, in column 4 I use a stricter definition of downsizing firms: a downsizing firm must see an employment reduction larger than 5 percent *compared to the previous year's level*.[19] This alternative instrumental variable is also summarized in Table 1.7. The F test gives a slightly lower statistic (21.6), the standard error is larger (0.164) and $\widehat{\beta_H}$ is no longer significant at 10 percent level. However, the point estimate is quite similar to that in the previous columns (0.231).

Recall the OLS estimates: (a) the coefficient on knowledgeable workers is 0.039 and (b) the coefficient on knowledgeable workers moving within the same two-digit industry is 0.072. In principle, the IV estimates (that are likely to be driven by flows *within* industries, given the way the instrument is designed) are consistent with the idea that the OLS coefficient is biased downward because of negative selection (lemons bias). In practice, however, the IV standard errors are large and prevent me from drawing definitive conclusions.

Another tentative explanation for the magnitude of the IV results is that the effect of knowledgeable workers may be heterogeneous across firms. If there are indeed heterogeneous effects of H on productivity, then consistent OLS measures the average effect of H on productivity across all firms, while Two Stage Least Squares (TSLS) estimates the average effect in the subset of firms that are marginal in the recruitment decision, in the sense that they recruit knowledgeable workers if and only if there exists excess local supply.[20] If the effect of knowledgeable workers on productivity is larger for non HWFs that are marginal in the recruitment decision, the TSLS estimates will exceed those of consistent OLS.

1.4.2 Sensitivity analysis

The main empirical result in the first part of the paper is that labor mobility from HWFs to other firms in the region works as a mechanism for the transfer of efficiency-enhancing knowledge. Table 1.9 shows results

[19] I keep the additional condition that the decrease in the labor force is greater than or equal to three individuals.

[20] See Imbens and Angrist (1994) for a discussion. For a recent example, see Eisensee and Strömberg (2007).

from a series of specification checks. As a basis for comparison, Column 1 shows the estimates from the baseline specification in Column 1 of Table 1.6. Considering the differences in observable characteristics documented in Section 1.3.2 between movers from HWFs and other workers at non HWFs, in Column 2 I augment Equation (1.3) with the share of females, managers, blue-collar and white-collar workers, and differently aged workers at each firm. The results largely remained unchanged.

Column 3 shows estimates using the within-transformation. These estimates should be interpreted cautiously because the within estimator is known from practical experience to perform poorly in the context of production functions (Eberhardt and Helmer, 2010). Indeed, estimates in Column 3 indicate severely decreasing returns to scale, likely due to measurement error in the input variables, whose influence is exacerbated by the variable transformation. The problem of using the within-transformation is the removal of considerable information from the data, since only variation over time is left to identify parameters. Setting this concern aside, the results show a positive and significant coefficient on H (0.012) that is smaller than the baseline OLS coefficient, and the coefficients in other specifications reported in Table 1.6.

Columns 4-5 investigate the role of functional form assumption. Until now, I have presented results based on specifications where the intensity of potential knowledge transferred is measured by the number of H workers. In Column 4, I model this intensity as the share of workers with recent experience at good firms, dividing H by L. The coefficient is positive and significant: a one percentage point increase in h is associated

with a change in productivity of 0.8percent.[21] In Column 5 I estimate:

$$\begin{aligned} \ln(Y_{jslt}) &= \beta_0 + \beta_L \ln(\overline{\theta}_{jslt} L_{jslt}) + \beta_K \ln(K_{jslt}) + \\ \beta_M \ln(M_{jslt}) + \beta_{H_l} \log(H_{jslt}) + \delta 1(H &= 0)_{jslt} + \mu_{st} + \varpi_{lt} + v_{jslt} \end{aligned}$$

Compared to Equation (1.3) I replaced H_{jslt} with its logarithm, and I imposed $\log(H_{jslt}) = 0$ for the observations with $H_{jslt} = 0$. Plus, I added the dummy $1(H = 0)_{jslt}$ taking value 1 if the number of knowledgeable workers is equal to 0. The results using this alternative functional form are again consistent with those discussed in the main text.

Finally, I address the issue of unobservables related with new hires. If workers who recently changed firms are more productive than stayers, the effect of newly hired workers with HWF experience may equally apply to newly hired employees without HWF experience. In order to explore this possibility I first define medium-wage-firms (MWFs) as those whose estimated firm fixed effects from the AKM model fall between the 33th percentile and the 67th percentile of all estimated firm effects, and low-wage-firms (LWFs) as those whose estimated firm fixed effects fall below the bottom third. I then construct two new variables. The first one, denoted with $\widetilde{H}$ is the number of workers with recent experience at HWFs currently observed at MWF m. I define a worker as having recent HWF-experience in year t, if he or she is observed working in a HWF for one or more of the years $t-5$ to $t-1$. If a worker is hired at time $t-g$, and has experience at a HWF between $t-g$ and $t-5$, she contributes to $\widetilde{H}$ count from year $t-g$ until t. [22] The second variable I construct,

[21] Since there may be measurement error in L, the number of employees in the AIDA data, a potential problem with such specification arises. Rewrite equation (1.3) as $\ln(\frac{Y_{jst}}{\overline{\theta} L_{jst}}) = \beta_K \ln(K_{jst}) + \beta_M \ln(M_{jst}) + \beta_h h_{jst} + \mu_{st} + \varpi_{lt} + v_{jslt}$. Since $h = H/L$, a mechanical relantionship between h and the dependent variable may arise at time t. To address this issue, I also use the lagged share of H workers obtained from head counts in the Social Security dataset. The coefficient estimate (not shown) is 0.650 (0.345).

[22] It may be instructive to consider a practical example. Consider a worker who separates from a HWF in 1992 and joins MWF m in 1995. Provided that the worker remains in j, she will be counted as a knowledgeable worker for every year from 1995 to 1997.

denoted with $\widetilde{N}$, is the number of workers with recent experience at LWFs currently observed at MWF m. I then estimate for the sample of MWFs:

$$\begin{aligned}\ln(Y_{mslt}) &= \beta_0 + \beta_L \ln(\overline{\theta}_{mslt} L_{mslt}) + \beta_K \ln(K_{mslt}) + \beta_M \ln(M_{mslt}) + \\ &\quad + \beta_{\widetilde{H}} \widetilde{H}_{mslt} + \beta_{\widetilde{N}} \widetilde{N}_{mslt} + \mu_{st} + \varpi_{lt} + v_{mslt}\end{aligned}$$

In this specification, the identification of knowledge transfer relies on the differential effect of hiring an employee with recent HWF experience over hiring an employee from a LWF. By including both $\widetilde{H}$ and $\widetilde{N}$, any potential bias caused by the correlation between unobservables and new hires is removed. Column 6 shows the results. The coefficient of $\widetilde{H}$ is positive (.041) and significant. The coefficient of $\widetilde{N}$ is positive but smaller (0.015) and not significant. The difference in productivity effects associated with each type of "movers" is significant at 10 percent level. The productivity effect attributed to knowledgeable workers, therefore, does not appear to be associated with recently hired workers in general. That large productivity gains linked to hiring seem to be realized only when new hires come from more productive firms is consistent with the knowledge spillovers hypothesis.

1.5 Conclusions

This chapter directly examined the role of labor mobility as a mechanism for the transfer of efficiency-enhancing knowledge. In order to empirically assess the importance of labor-market based knowledge spillovers, I used Social Security earnings records and detailed financial information for firms from the Veneto region of Italy. The regression analysis showed that hiring a worker with HWF experience increases the productivity of other (non-HWF) firms. The next chapter evaluates the extent to which labor mobility can explain the productivity advantages of firms located near other highly productive firms.

1.6 Figures and Tables

Figure 1.1: *Distribution of Firm Effects*

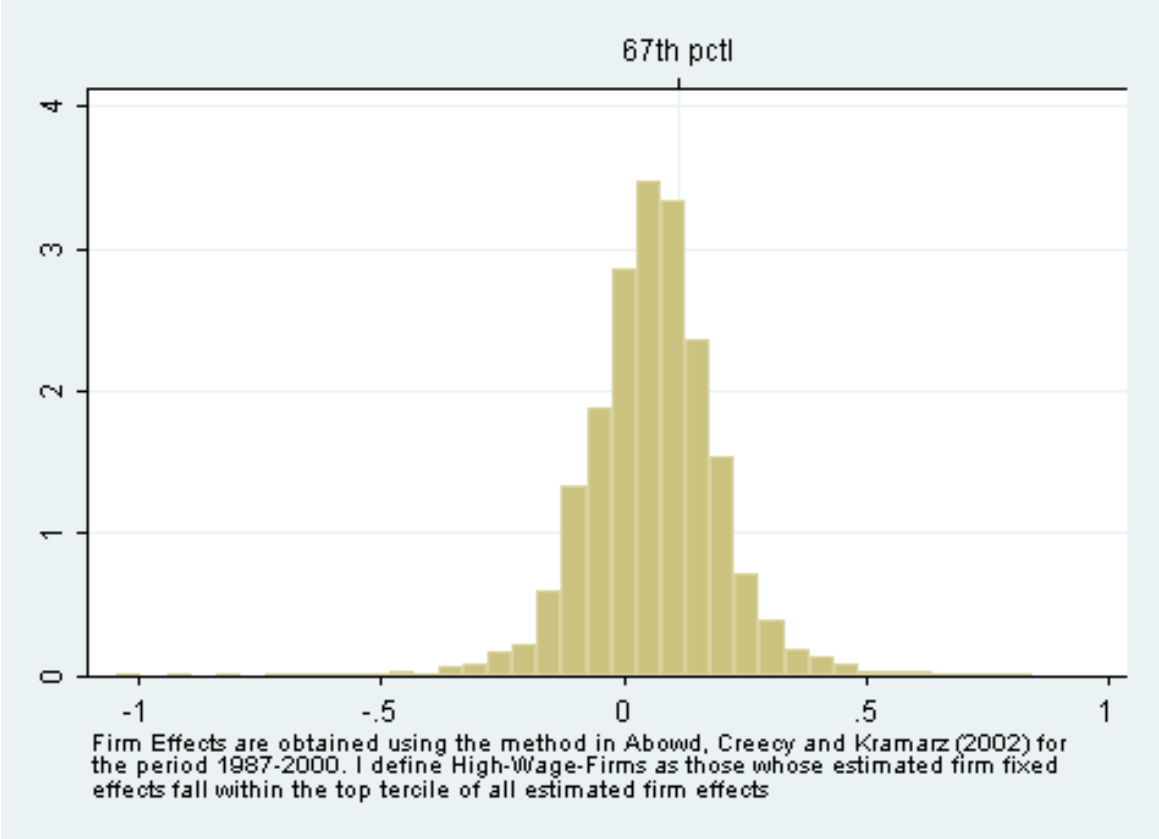


Table 1.1: Characteristics of HWFs, 1995-2001

	(1) Y/L	(2) VA/L	(3) K/L	(4) Tangible K/L	(5) Intangible K/L
HWF	0.150	0.113	0.104	0.066	0.270
	(0.017)	(0.012)	(0.025)	(0.027)	(0.042)
Observations	26041	26041	26041	26041	26041
Adj. R-squared	0.160	0.106	0.181	0.187	0.0644

Dependent Variables are in logs. All OLS regressions include year and 4-digit industry dummies. Output, Value Added and Capital variables are in 1000's of 2000 euros. Standard errors (in parentheses) clustered by firm. The dummy HWF takes value 1 if the firm is classified as high-wage after estimating the AKM model on the period 1987-2000.

Table 1.2: non-HWFs, Main Estimation Sample

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**	**N**
Output	8205.547	(9085.215)	1086.012	83537.188	17937
Capital	1829.342	(2400.112)	57.222	20876.002	17937
materials	4148.033	(5403.845)	68.405	47337.867	17937
value added	2088.875	(2293.955)	-4082.134	34466.188	17937
Tangible Capital	1691.601	(2265.701)	2.833	20668	17937
Intangible Capital	137.741	(382.714)	0	11837.857	17937
employees from AIDA	48.069	(47.239)	2	420	17937
employees from VWH	49.173	(45.404)	11	458	17937
apprentices	1.033	(2.004)	0	47	17937
blue collars	30.178	(30.144)	0	348	17937
white collars	9.638	(11.927)	0	251	17937
managers	0.662	(1.855)	0	54	17937
female employees	13.157	(18.874)	0	309	17937
employees age$<$ 30	13.988	(13.499)	0	201	17937
employees age$>$ 45	9.128	(12.893)	0	199	17937
H workers	0.071	(0.302)	0	7	17937
H workers same Ind	0.021	(0.161)	0	5	17937
H workers diff Ind	0.051	(0.245)	0	7	17937
H managers	0.003	(0.053)	0	2	17937
H white collars	0.024	(0.164)	0	3	17937
H blue collars	0.044	(0.231)	0	6	17937

Sample includes 3661 Individual Firms in the period 1995-2001. Output, Capital, Materials, Value Added are in thousands of 2000 euros. Employees from AIDA refers to the values found in the AIDA balance sheet data. Employees from VWH refers to the values obtained from head count in the Veneto Worker History data from Social Security.

Table 1.3: Characteristics of HWFs Workforce, 1987-2001

	(1) share white coll.	(2) share manager	(3) share female	(4) share age<30	(5) share age>45
HWF	0.018	0.003	-0.031	0.000	-0.006
	(0.004)	(0.001)	(0.005)	(0.005)	(0.004)
Observations	58102	58102	58102	58102	58102
Adj. R-squared	0.226	0.103	0.569	0.167	0.140

All OLS regressions include year and 4-digit industry dummies. Standard errors (in parentheses) clustered by firm. The dummy HWF takes value 1 if the firm is classified as high-wage after estimating the AKM model on the period 1987-2000.

Table 1.4: Characteristics of Knowledgeable Workers observed at non-HWFs, 2001

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**	**N**
age	33.813	(8.481)	18	62	407
female	0.251	(0.434)	0	1	407
blue collar	0.548	(0.498)	0	1	407
white collar	0.388	(0.488)	0	1	407
manager	0.049	(0.216)	0	1	407

Table 1.5: Characteristics of Workers without HWF experience observed at non-HWFs, 2001

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**	**N**
age	37.08	(9.538)	16	65	192588
female	0.32	(0.467)	0	1	192588
blue collar	0.71	(0.454)	0	1	192352
white collar	0.242	(0.428)	0	1	192352
manager	0.023	(0.15)	0	1	192352

Table 1.6: H Workers and Productivity in non-HWFs, Main Estimates, 1995-2001

	(1) OLS	(2) OP	(3) LP	(4) Inv-Cap Interact.	(5) Inv-Mat Interact.	(6) Same/Diff Industry
log(capital)	0.097	0.093	0.149	0.000	0.000	0.097
	(0.005)	(0.020)	(0.010)	(0.000)	(0.000)	(0.005)
log(materials)	0.571	0.576		0.591	-3.878	0.571
	(0.008)	(0.009)		(0.014)	(0.510)	(0.008)
log(employees)	0.235	0.235	0.204	0.212	0.181	0.235
	(0.008)	(0.009)	(0.006)	(0.014)	(0.006)	(0.008)
H workers	0.039	0.037	0.020	0.039	0.022	
	(0.008)	(0.011)	(0.006)	(0.020)	(0.009)	
H from same Ind						0.072
						(0.018)
H from diff Ind						0.024
						(0.009)
$\beta_H^{same} = \beta_H^{diff}$,pv						0.018
Observations	17937	6892	17937	3063	14120	17937
Adj. R-squared	0.924			0.930	0.948	0.924

Dependent variable: Log(Output). Standard errors (in parentheses) clustered by firm. H workers is the number of workers with HWF experience currently observed at non-HWFs. Column 1 reports estimates from the baseline specification. Column 2 implements the procedure in Olley and Pakes (1996). Column 3 implements the procedure in Levinsohn and Petrin (2003). Column 4 adds a third-degree polynomial function of log capital and log investment and the interaction of both functions in t and t+1. Column 5 includes the same controls as col. 5 but replaces log investment with log materials. Column 6 differentiates between workers moving within the same industry and between industries. $\beta_H^{same} = \beta_H^{diff}$,pv is the p-value of the equality of coefficients of the variable 'H from same Ind' and the variable 'H from diff Ind'.

Table 1.7: Instrumental Variables: Summary Statistics, 1995-2001

Variable	Mean	(Std. Dev.)	Min.	Max.	N
lag (downsizing HWFs, $>$ 3 percent)	0.33	(0.973)	0	7	17937
lag (downsizing HWFs, $>$ 5 percent)	0.307	(0.909)	0	7	17937

The variable 'lag (downsizing HWFs, $>$ 3 percent) ' is the lagged number of downsizing local good firms in a given 5-digit industry. A good firm is considered as downsizing if the drop in L is larger than 3 percent. The decrease in the labor force must also be greater than or equal to three individuals. In constructing the variable 'downsizing HWFs, $>$ 5 percent' a good firm is considered as downsizing if the drop in L is larger than 5 percent.

Table 1.8: Knowledgeable Workers and Productivity in non-HWFs, IV Estimates 1995-2001

	(1) Baseline	(2) tradability	(3) localization	(4) 5 percent
H workers	0.268	0.269	0.278	0.231
	(0.154)	(0.154)	(0.145)	(0.164)
log(capital)	0.095	0.095	0.094	0.095
	(0.005)	(0.005)	(0.005)	(0.006)
log(materials)	0.568	0.568	0.568	0.568
	(0.010)	(0.010)	(0.010)	(0.010)
log(employees)	0.227	0.227	0.227	0.229
	(0.010)	(0.010)	(0.010)	(0.010)
Observations	17937	17937	17937	17937
Adj. R-squared	0.908	0.908	0.907	0.910
Fstat, instrum., 1st stage	23.06	23.14	24.41	21.55

Dependent variable: Log(Output). Standard errors (in parentheses) clustered by LLM (47). Regressions include industry-year interaction dummies and LLM-year interaction dummies. Column 1 reports IV estimates using the lagged number of downsizing local good firms in the same 5-digit industry. A good firm is considered as downsizing if the drop in L is larger than 3 percent. The decrease in the labor force must also be greater than or equal to three individuals. Column 2 adds an indicator of the importance of local demand, namely a dummy taking value 1 if the 4-digit industry produces goods that are not widely traded outside the LLM. Column 3 controls for an index of industry localization, namely the ratio between the number of firms in Veneto and total Italian firms in a given 4-digit industry. In Column 4 a good firm is considered as downsizing if the drop in L is larger than 5 percent.

Table 1.9: Knowledgeable Workers and Productivity in non-HWFs, Robustness to Different Specifications

	(1) Baseline OLS	(2) Workforce Characteristics	(3) Within	(4) Share	(5) Log	(6) Recent Experience
log(capital)	0.097	0.093	0.066	0.097	0.097	0.095
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
log(materials)	0.571	0.561	0.586	0.571	0.571	0.565
	(0.008)	(0.008)	(0.015)	(0.008)	(0.008)	(0.012)
log(employees)	0.235	0.243	0.064	0.238	0.235	0.251
	(0.008)	(0.008)	(0.005)	(0.008)	(0.008)	(0.012)
H workers	0.039	0.034	0.012			
	(0.008)	(0.008)	(0.005)			
share H workers				0.765		
				(0.171)		
log(H workers)					0.066	
					(0.030)	
No H workers					-0.040	
					(0.011)	
Recent HWF exp						0.041
						(0.010)
Recent LWF exp						0.015
						(0.011)
$\beta_{\widetilde{H}}^{HWF} = \beta_{\widetilde{N}}^{LWF}$,pv						0.092
Observations	17937	17937	17937	17937	17937	9269
Adj. R-squared	0.924	0.925	0.985	0.924	0.924	0.932

Dependent variable: Log(Output). Standard errors (in parentheses) clustered by firm. Regressions include industry-year interaction dummies and LLM-year interaction dummies. The variable 'H workers' is the number of knowledgeable workers currently observed at non-HWFs. The variable 'log(H workers)' is the logarithm of number of knowledgeable workers. The dummy 'No H workers' takes value 1 if the number of knowledgeable workers is equal to 0. The variable 'Recent HWF exp' is the number of workers currently observed at Column 1 reports estimates from the baseline specification. Column 2 adds the shares of managers, white collars, blue collars, females, and differently aged workers. Column 3 reports within estimates. Column 4 replaces the number of H workers with the share of H workers. Column 5 replaces the number of H workers with the log of H workers plus the dummy 'No H workers'. Column 6 is estimated on the sample of MWFs and includes workers with recent experience at HWF and Low-Wage-Firms (LWFs). $\beta_{\widetilde{H}}^{HWF} = \beta_{\widetilde{N}}^{LWF}$,pv is the p-value of the equality of coefficients of the variable 'Recent HWF exp' and the variable 'Recent LWF exp'

1.7 Appendix to Chapter 1

1.7.1 Data: Sample Restrictions and Additional Descriptive Information

I use firm identifiers to match job-year observations for workers aged 16-64 in the VWH with firm financial data in AIDA for the period 1995-2001. The match rate is fairly high: at least one observation in the VHW was found for over 95 percent of the employers in the AIDA sample, and around 50 percent of employees observed in the VWH between 1995 and 2001 can be matched to an AIDA firm. Most of the nonmatches seem to be workers of small firms that are omitted from AIDA. In sum, I was able to match at least one employee for around 18,000 firms, or around 10 percent of the entire universe of employers contained in the VWH.[23] From this set of potential matches I execute two exclusions to obtain my estimation sample for Equation (1.7). First, I remove all workers outside manufacturing. Next, I exclude job-year observations with remarkably high or low values for wages (I trim observations outside the 1 percent - 99 percent range).

The method in Abowd, Creecy and Kramarz (2002) identifies separate groups of workers and firms that are connected via labor mobility in the data. I run the grouping algorithm separately using VHW data from 1987 to 2000 for firms that could be matched in AIDA and have more than 10 employees in VHW. I then use the created group variable to choose the largest group as the sample for my fixed-effects estimation. The largest group contains 99.1 percent of the woker-year observations (2,567,040 observations combining 457,763 individuals with 5,937 firms). I identify HWFs as those firms whose firm effects rank in the top third of the sample.[24] Table 1.3 illustrates workforce characteristics of HWFs

[23] Card, Devicienti and Maida (2011) show that the average firm size for the matched jobs sample (36.0 workers) is considerably larger than that for total employers in the VWH (7.0 workers). Mean daily wages for the matched observations are also greater, while the fractions of under 30 and female employees are lower.

[24] In order to implement the approach in Abowd, Creecy and Kramarz (2002), I use the a2reg Stata routine developed by Ouazad (2007).

and non HWFs. [25]

The sample of non HWFs used in the main firm-level analysis – equation (1.3) - is summarized in Table 1.2.[26] The main analysis is performed over the period for which balance sheet data are available (1995-2001). Notice the overlap with the period over which Equation (1.7) is estimated (1987-2000). In principle one would like to perform the two estimations - Equation (1.7) and (1.3) - on two different samples. However, in practice the AKM routine requires a large number of events of labor mobility in order for the firm and worker effects to be identified. Moreover, to precisely estimate $\widehat{\beta_H}$ one would like to exploit as much variation as possible in H, i.e. as many moves from good firms to other firms as possible. Choosing 2000 as the end period for the first estimation seems a good compromise because (a): it guarantees a long enough panel for the AKM estimation, (b) it allows consideration of all the possible moves from good firms to other firms (including in particular workers who separate from good firms in 2000 and are observed in other firms in 2001) and (c) still prevents a full overlapping between the two sample periods for the two different estimations. I experimented with other choices for the period of the AKM estimation, such as 1986-2000 or 1987-1999. Results are very similar and available upon request.

[25] Notice that since the specifications in Table 1.3 do not require information collected from AIDA balance sheets, the sample period is not restricted to post-1995 observations.

[26] In order to obtain this firm-level estimation sample I first remove the HWFs. From this non-HWF sample I remove (a) firms that close during the calendar year and (b) firm-year observations with remarkably high or low values (outside the 1% - 99% range) for several key firm-level variables, such as total value of production, number of employees, capital stock and value of materials. (c) firms in LLM with centroids outside Veneto (3 LLMs). I then attempt to reduce the influence of false matches, particularly for larger firms, by implementing a strategy of Card, Devicienti and Maida (2011) to eliminate the "gross outliers", a minor number of matches (less than 1% of all employers) for which the absolute gap between the number of workers reported in a firm's AIDA balance sheet and the number found in the VWH is larger than 100.

1.7.2 Non-Tradable Goods

In Column 2 I added a dummy taking value one if the industry produces goods that are not widely traded outside the LLM. Industries for which the dummy takes value one are those classified as SMSA industries by Weiss (1974): Bottled and Canned Soft Drinks and Carbonated, Mineral, and Plain Waters; Fluid Milk; Bread and Other Bakery Products, Except Cookies and Crackers; Manufactured Ice; Primary Forest Products; Newspapers; Commercial Printing (except Lithographic); Commercial Printing (Lithographic); Engraving and Plate Printing; Typesetting; Photo-Engraving; Electrotyping and Stereotyping; Ready-Mix Concrete.

Chapter 2

Worker flows and Agglomeration Advantages

2.1 Introduction

In this Chapter, I assess the extent to which worker flows can explain the productivity advantages of firms located near other highly productive firms. I relate my findings to the existing evidence on the productivity advantages of agglomeration, focusing in particular on the study performed in Greenstone, Hornbeck and Moretti (2010, henceforth GHM).

The authors find that after the opening of a large manufacturing establishment, total factor productivity (TFP) of incumbent plants in US counties that were able to attract one of these large plants increases significantly relative to the TFP of incumbent plants in counties that survived a long selection process but narrowly lost the competition. The observed effect on TFP is larger if incumbent plants are in the same industry as the large plant, and increases over time. These two facts are consistent with the presence of intellectual externalities that are embodied in workers who move from firm to firm. However, data limitations prevent GHM from drawing definitive conclusions regarding the driving mechanism.

I evaluate the extent to which worker flows explain empirical evidence on the productivity advantages of agglomeration by simulating an event similar to that studied by GHM but within the worker mobility frame-

work described above. The change in productivity predicted within this framework equals 10-15 percent of the overall effect found in GHM, indicating that knowledge transfer through worker flows explain a significant portion of the productivity advantages through agglomeration.

2.2 Context

2.2.1 Relation to Previous Research

This study adds to the growing literature on productivity advantages through agglomeration, a literature critically surveyed in Duranton and Puga (2004), Rosenthal and Strange (2004) and Moretti (2011). The research relating most closely to my study is the body of work on microfoundations for agglomeration advantages based on knowledge spillovers.

In Combes and Duranton (2006)'s theoretical analysis, firms clustering in the same locality face a trade-off between the advantages of labor pooling (i.e. access to knowledge carriers) and the costs of labor poaching (i.e. loss of some key employees to competitors along with higher wage bills to retain other key employees).

In a case study of the British Motor Valley, Henry and Pinch (2000) conclude that

> as personnel move, they bring with them knowledge and ideas about how things are done in other firms helping to raise the knowledge throughout the industry...The crucial point is that whilst this process may not change the pecking order within the industry, this 'churning' of personnel raises the knowledge base of the industry *as a whole within the region*. The knowledge community is continually reinvigorated and, synonymous with this, so is production within Motor Sport Valley

In a similar vein, Saxenian (1994) maintains that the geographic proximity of high-tech firms in Silicon Valley is associated with a more

efficient flow of new ideas. I contribute to the literature on micro-foundations for agglomeration advantages by showing direct evidence of productivity gains through worker flows.

My results are consistent with the findings by Henry and Pinch (2000). Since worker flows in a local labor market are larger within an industry, and, as I shall show, the productivity effect is larger for workers moving within the same industry, my results may also help explain the findings in Henderson (2003), Cingano and Schivardi (2004) and Moretti (2004a) that local spillovers are increasing in economic proximity (Measures of economic links include input and output flows and indicators of technological linkages).

Some research beyond the agglomeration literature has also emphasized the fact that new workers share ideas on how to organize production or information on new technologies that they learned with their previous employer. Balsvik (2011) uses matched employer-employee data from Norway and offers a detailed account of productivity gains linked to worker flows from foreign multinational to domestic firms.[1] Similarly, using linked worker-firm data, Parrotta and Pozzoli (2012) and Stoyanov and Zubanov (2012) show evidence from Denmark that is consistent with models of knowledge diffusion through labor mobility.

My findings are consistent with those of these three recent papers. My empirical strategy, however, allows me to make progress on the identification of the causal effect of recruiting knowledgeable workers on productivity.

As shown above, I address the three main identification issues, namely (a) unobservable contemporaneous productivity shocks at time t, (b) unobservable worker quality and (c) unobservable future productivity shocks, using several approaches, including control function methods from the recent productivity literature and an IV strategy.

Furthermore, while the above authors focus exclusively on the role of labor mobility for knowledge transfer, I seek to shed light on a broader question: the extent to which labor mobility can explain evidence on the productivity advantages through agglomeration.

[1] Poole (2012) finds a positive effect on wages paid in domestic firms in Brazil of the share of new workers previously employed by foreign-owned firms.

Finally, Veneto is a very interesting laboratory to investigate the topic of labor-market based knowledge spillovers because this region is part of a larger economic area of Italy where, as in the Silicon Valley, networks of specialized small and medium-sized firms, frequently organized in districts, have been effective in promoting and adapting to technological change during the last three decades. The next section provides more details regarding this aspect.

2.2.2 The interesting laboratory of Third Italy

While the issues analyzed in this study are of general interest, the case of Veneto is important because this region is part of a larger economic area of Italy where networks of specialized small and medium-sized firms, frequently organized in districts, have been effective in promoting and adapting to technological change during the last three decades. This so called "Third Italy" region has received a good deal of attention by researchers, in the United States as well as in Europe (Brusco, 1983; Piore and Sabel, 1984; Trigilia, 1990; Whitford, 2001; Piore, 2009).

Indeed, a growing body of work analyzes the dynamics of regional network-based industrial systems, which have been identified in many areas of the Western world at different points in time. In these systems, which are based on horizontal networks of firms, producers expand their own know-how "by specializing while engaging in close but not exclusive relations with other specialists" (Saxenian, 1994). The industrial districts of Third Italy are, together with the Silicon Valley, the most studies examples of regional network-based systems.[2]

More specifically, the dynamic regional economy of Veneto features a large presence of flexible firms, frequently organized in districts with a level of industrial value added greatly exceeding the national average. The most famous industrial concentration is the eyewear district in the province of Belluno, where Luxottica, the world's largest manufacturer of eyeglasses, has production plants.

[2] Germany's Baden-Wurttermberg is also known "for its mix of small and medium-sized makers of machine tools, textile equipment, and automobile components alongside giant electronics corporations" (Saxenian, 1994, p. 7)

Manufacturing firms in Veneto specialize in metal-engineering, goldsmithing, plastics, furniture, garments, textiles, leather and shoes. Benetton, Sisley, Geox, Diesel, and Replay are Venetian brands. The manufacture of food and beverage, and wine and baked goods in particular, is also a prominent subsector. Since the mid-1980s, the labor market in Veneto has been characterized by nearly full employment, a positive rate of job creation in manufacturing and positive migration flows (Tattara and Valentini, 2010).

2.3 Overview of the Methodology

My goal is to assess the extent to which worker flows can explain the productivity advantages of firms located near other highly productive firms. In order to do so, I simulate an event analogous to that studied by GHM but within my framework, and I predict the change in local productivity that is due to labor mobility.

The event I simulate is an increase in the number of good firms such that the change in local output is comparable to the output of the average large plant whose opening is considered by GHM. The large plants in GHM generated bidding from local governments, almost certainly because there was a belief of important positive effects on the local economy. GHM observe that the mean increase in TFP after the opening is (a) increasing over time and (b) larger if incumbent plants have the same industrial classification as the large plant. These two facts are consistent with the presence of intellectual externalities that are embodied in workers who move from firm to firm. I think of the plants considered by GHM as "good" plants, and in order to simulate their experiment I consider a change in the number of Veneto good firms such that the change in local output is comparable.

An overview of my procedure is as follows.

Denote the number of knowledgeable workers *moving within industry* observed at firm j with H^{ind}. As a first step, I estimate the effect on H_j^{ind} of a change in the number of good local firms within the same industry as j. If a worker is hired from a HWF in the same industry at time $t-g$, she contributes to H_j^{ind} from year $t-g$ until t. It may

be instructive to consider a practical example. Consider a worker who joins HWF j in 1995 after separating from a HWF in 1992. If the worker remains in j until 2000, she will contributes to H_j^{ind} count for every year from 1995 to 2000.

The above implies that H^{ind} exhibits a certain degree of persistence and suggests estimation of a dynamic model for the number of workers observed at firm j who have HWF experience in the same industry.

In the second step, I predict the change in H^{ind} that each of the non HWFs in a LLM would experience if an output increase similar to the one considered by GHM were to occur, and I multiply the predicted change in H^{ind} by $\widehat{\beta_H}^{ind}$, the estimated coefficient on H^{ind} in my productivity regression. This product yields the predicted change in productivity due to worker flows for a given Veneto firm if its locality and industry were to experience an increase in output analogous to that considered by GHM.

In the final step, I compare my estimate of the predicted contribution of worker flows to productivity changes with GHM's estimate of the overall productivity effect. This comparison allows me to have a sense of the extent to which worker flows can explain the productivity gains experienced by other firms when high-productivity firms in the same industry are added to a local labor market.

In Section 2.4.2 I discuss the issues related to the implementation of the first step, i.e. the estimation of the dynamic effect on H_j^{ind} of a change in the number of good firms in the same locality and industry.

2.4 A closer look at the mobility of knowledgeable workers

2.4.1 The Role of Geographical Proximity: Further Discussion

There exist at least two reasons why geographic proximity might be important for observed worker flows. First, distance may act as a barrier for workers' job mobility because of commuting costs or idiosyncratic preferences for location.

Descriptive statistics in Combes and Duranton (2006) show that labor flows in France are mostly local: about 75% of skilled workers remain in the same employment area when they switch firms. The degree of geographical mobility implied by this figure is small, since the average French employment area is comparable to a circle of radius 23 kilometers.

In Dal Bo', Finan and Rossi (2013), randomized job offers produce causal estimates of the effect of commuting distance on job acceptance rates. Distance appears to be a very strong (and negative) determinant of job acceptance: applicants are 33% less likely to accept a job offer if the municipality to which they are assigned is more than 80 kilometers away from their home municipality. The estimates in Manning and Petrongolo (2013) also suggest a relatively fast decay of job utility with distance.

Another reason geographical proximity may be an important determinant of job mobility is that the firm's informational cost of identifying the "right" employee are larger across localities than within them. A similar argument can be made for the informational costs for workers.

2.4.2 A dynamic model for the number of knowledgeable workers

Consider a model of the form

$$H_{jlst}^{ind} = aH_{jsl,t-1}^{ind} + bGood_Firms_{ls(j)t} + e_{jlst} \tag{2.1}$$

$$e_{jlst} = m_j + v_{jlst}$$

$$E[m_j] = E[v_{jlst}] = E[m_j v_{jlst}] = 0 \tag{2.2}$$

where $Good_Firms_{ls(j)t}$ is the number of local good firms in the same industry of firm j. Figure 2.1 shows the geographical variation in the number of HWFs across LLMs for the most recent year (2001).

Recall that the subscript ind represent workers moving within industry. The disturbance term e_{jlst} has two orthogonal components: the firm effect, m_j and the idiosyncratic shock, v_{jlst}. Using OLS to estimate Equation (2.1) is problematic because the correlation between $H_{jsl,t-1}^{ind}$ and the firm effect in the error term gives rise to "dynamic panel bias" (Nickell, 1981). Application of the Within Groups estimator would draw

the firm effects out of the error term, but dynamic panel bias would remain (Bond, 2002).

Therefore I employ the first-difference transform, proposed by Arellano and Bond (1991):

$$\Delta H^{ind}_{jlst} = a\Delta H^{ind}_{jsl,t-1} + b\Delta Good_Firms_{ls(j)t} + \Delta v_{jlst} \qquad (2.3)$$

The firm effects have now disappeared, but the lagged dependent variable is still potentially endogenous as the $H^{ind}_{jsl,t-1}$ in $\Delta H^{ind}_{jsl,t-1} = H^{ind}_{jsl,t-1} - H^{ind}_{jsl,t-2}$ is correlated with the $v_{jls,t-1}$ in $\Delta v_{jlst} = v_{jls,t} - v_{jls,t-1}$. However, longer lags of the regressors remain orthogonal to the error and are available for use as instruments. Natural candidate instruments for $\Delta H^{ind}_{jsl,t-1}$ are $H^{ind}_{jsl,t-2}$ and $\Delta H^{ind}_{jsl,t-2}$. Both $H^{ind}_{jsl,t-2}$ and $\Delta H^{ind}_{jsl,t-2}$ are mathematically related to $\Delta H^{ind}_{jsl,t-1} = H^{ind}_{jsl,t} - H^{ind}_{jsl,t-1}$ but not to the error term $\Delta v_{jlst} = v_{jls,t} - v_{jls,t-1}$, provided that the v_{jlst} are not serially correlated. Arellano and Bond (1991) develop a test for autocorrelation in the idiosyncratic disturbance term v_{jlst}. It checks for serial correlation of order l in levels by looking for correlation of order $l+1$ in differences. I employ this test below.

In principle, another challenge in estimating (2.3) is that firms in a given industry do not select their location randomly. Firms maximize profits and decide to locate where their expectation of the present discounted value of future profits is greatest. This net present value differs across locations depending on many factors, including transportation infrastructure, subsidies, etc. These factors, whose value may be different for firms in different industries, are unobserved, and they may be correlated with ΔH^{ind}_{jlst}.

It should be noted, however, that a positive shock in LLM j and industry s such that there is entry of HWFs (i.e. an increase in $\Delta Good_Firms_{ls(j)t}$) makes it *less* likely that a non HWFs is going to hire from a good firm in the same industry. This is because the shock is *good news* for good firms, so in principle it should make it less likely for the labor force at the good firms to experience a decrease, and in turn, it should make it less likely for a non HWF to hire from a good firm. The bias introduced by the fact that good firms do not choose their location randomly is therefore likely to be downwards, and thus working against the finding of a positive ef-

fect of $\Delta Good_firms_{ls(j)t}$ on ΔH^{ind}. In any case, $\Delta Good_Firms_{ls(j)t}$ is treated as endogenous in the estimation.

Table 2.1 gives the results of estimating Equation (2.3) for the period 1989-2001. I include time dummies in order to remove universal time-related shocks from the errors. Since these specifications do not require information collected from AIDA balance sheets, the sample period is not restricted to post-1995 observations.

Column 1 uses the classic Arellano-Bond Difference GMM estimator and shows a positive (0.004) and significant coefficient of the number of good local firms. This is in line with the idea discussed above of an important role of geographic and economic proximity in determining worker mobility. Column 1 also shows a positive (0.231) and significant coefficient for the lagged dependent variable. The p-value of the Hansen test for overidentifying restrictions does not suggest misspecification. The Arellano-Bond test for serial correlation fails to indicate that the v_{jlst} are serially correlated.

Columns 2 to 4 investigate the robustness of these estimates to different specifications.

I begin by using a different transform, proposed by Arellano and Bover (1995), namely the "forward orthogonal deviations" transform. Rather than subtracting the observation in $t-1$ from the observation in t, the orthogonal deviations transform subtracts the average of all future available observations of a variable. This has the advantage of reducing data loss because, no matter how many gaps, it is computable for each firm. Since I remove all firm-year observations with remarkably high or low values for the number of employees, my estimation panel indeed has some gaps, which are magnified by the first-difference transform. (If some H_{jlst} is missing, for example, then both ΔH_{jlst} and ΔH_{jlst+1} are missing in the first-differenced data.).

I then estimate the model with two-step GMM and Windmeijer (2005)-corrected cluster-robust errors. See Roodman (2009) for a detailed discussion of two-step GMM and Windmeijer-correction.

Finally I estimate the model with two-step GMM, Windmeijer-corrected standard errors and orthogonal deviations. The estimates in Columns 2 to 4 are similar to those in Column 1.

2.5 Simulation Results

Having estimated the dynamic effect on H_j^{ind} of a change in $Good_Firms_{ls(j)t}$, I can predict the changes in H, and hence in productivity, that a given non-HWF in Veneto would experience after an output increase similar to the one considered by GHM. As it turns out, the large manufacturing plants whose openings are studied by GHM are much larger than the typical good firm in Veneto. This is due both to the fact that new entrants in GHM are significantly larger than the average new plant in the United States and the fact that the Veneto region is characterized by the presence of small and medium-sized businesses, whose size is smaller than the typical firm in United States

Table 1 in GHM reports statistics for the sample of plants whose opening is considered in their study. These plants are quite large: they are more than twice the size of the average incumbent plant and account for roughly nine percent of the average county's total output one year prior to their opening. The mean output (five years after their assigned opening date) is 452,801, 000 of year-2006 dollars, or 395,476,000 of 2000 euros. Standard deviation is 901,690, 000 of year-2006 dollars. As explained in the notes of Table 1 in GHM, these statistics are for a subset of the 47 plant openings studied by the authors. In particular, a few very large outlier plants were dropped so that the mean would be more representative of the entire distribution (those dropped had output greater than half of their county's previous output and sometimes much more).

In order to observe a change in local output comparable to the typical output increase caused by the opening of one large plant in GHM, a Veneto locality must experience an increase of 56 HWFs. This is the shock in my simulation.

The predicted change in H that each non-HWF would experience after 5 years, the time horizon considered in GHM, is then $\widehat{\Delta H}^{ind,5\ years} = 56 \cdot (b + ab + a^2b + a^3b + a^4b + a^5b)$. This change in H can be obtained using the estimates for a and b from Table 2.1.

In order to obtain the predicted change in productivity, I first obtain $\widehat{\beta_H}^{ind}$ by estimating Equation (1.3) after replacing H_j with H_j^{ind}. The

results using the different approaches (baseline OLS, OP, LP, polynomial functions of capital and investments or capital and materials in t and $t+1$) are shown in Table 2.2.

Using the baseline OLS productivity regression, estimated in Column 1 of Table 2.2, the predicted change in productivity attributable to worker flows five years the local output increase is equal to $\widehat{\Delta TFP}^{ind,5\ years} = \widehat{\Delta H}^{ind,5\ years} \cdot \widehat{\beta_H}^{ind,OLS} = 0.022$.

The final step is to compare the magnitude of $\widehat{\Delta TFP}^{ind,5\ years}$ with GHM's estimate of the overall productivity effect caused by a local output increase. The increase in productivity estimated by GHM five years after the opening for incumbent plants in the same two-digit industry equals 17 percent. Hence, my back-of-the-envelope calculations suggest that worker flows explain 13.3 percent of the agglomeration advantages estimated by GHM. Replacing $\widehat{\beta_H}^{ind,OLS}$ with $\widehat{\beta_H}^{ind,LP}$, the average effect of recruiting a knowledgeable worker with experience in the same industry estimated in the LP specification (Column 3 of Table 2.2), the contribution of worker flows to the agglomeration advantages estimated by GHM is equal to 8.1 percent.

Overall, the results in this section uggest that worker flows explain an economically relevant proportion of the productivity gains experienced by other firms when HWFs in the same industry are added to a local labor market.

2.6 Conclusions

Identifying the microeconomic mechanisms underlying localized productivity spillovers is crucial for understanding agglomeration economies. Without knowing the precise nature of the interactions between firms and workers that generate agglomeration advantages, it is difficult to be confident about the existence of any such advantages.

Additionally, pinpointing the ultimate causes of agglomeration advantages is helpful for understanding differences in productivity across industry clusters and localities.

Finally, better knowledge of the sources of the productivity advan-

tages of agglomeration is important for determining the optimal design of location-based policies.

This chapter evaluated the extent to which labor mobility can explain the productivity advantages of firms located near other highly productive firms. In order to empirically assess the importance of labor-market based knowledge spillovers, I used Social Security earnings records and detailed financial information for firms from the Veneto region of Italy.

The empirical evidence presented in this chapter points to the concrete possibility that agglomeration of economic activity creates important productivity advantages at the local level.

The productivity benefits of a non-HWF from being located in a cluster with a large number of good firms rest with the opportunities to hire workers whose knowledge was gained in good firms. Such knowledge can be successfully adapted internally. More specifically, the regression analysis showed that hiring a worker with HWF experience increases the productivity of other (non-HWF) firms. A simulation indicated that worker flows explain 10-15 percent of the productivity gains experienced by other firms when HWFs in the same industry are added to a local labor market.

2.7 Figures and Tables

Figure 2.1: *Distribution of HWFs across Local Labor Markets (LLMs)*

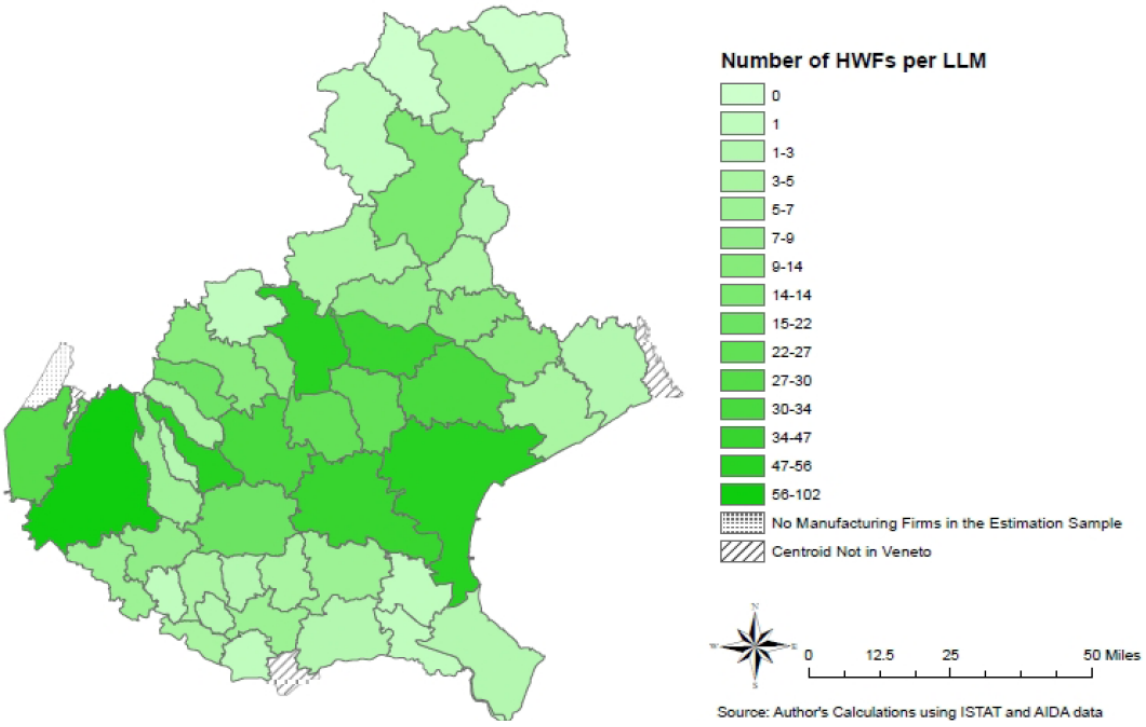


Table 2.1: Number of local HWFs in same Industry and Knowledgeable Workers moving within industry, GMM Estimates, 1989-2001

	(1) Baseline	(2) Deviations	(3) Two-step	(4) Deviations/ Two-step
lag(H from same Ind)	0.231	0.355	0.150	0.208
	(0.079)	(0.122)	(0.081)	(0.115)
Local HWFs in same Ind	0.004	0.003	0.003	0.002
	(0.002)	(0.001)	(0.001)	(0.001)
Observations	29554	29933	29554	29933
AR(1)z	-6.164	-5.053	-5.244	-4.063
AR(2)z	0.109	0.458	-0.405	-0.237
HansPv	0.272	0.366	0.272	0.366

Dependent variable: 'H from same Ind', the number of H workers moving within Industry. Cluster-robust standard errors in parentheses. Regressions include year dummies. Column 1 reports the baseline Difference GMM results. Column 2 uses the 'forward orthogonal deviations' transform, proposed by Arellano and Bover (1995). Column 3 estimates the model with two-step GMM and Windmeijer-corrected standard errors. Column 4 estimates the model with two-step GMM, Windmeijer-corrected standard errors and orthogonal deviations. The variable 'Local HWFs in same industry' is treated as endogenous. AR(1)z and AR(2)z: Arelanno and Bond (1999) test of first and second order serial correlation, distributed as N(0,1). HansPv: p-value of Hansen test of overidentifying restrictions. For all variables only the shortest allowable lagged is used as instrument.

Table 2.2: Knowledgeable Workers with experience in the same industry and Productivity in non-HWFs, 1995-2001

	(1) Baseline OLS	(2) OP	(3) LP	(4) Inv-Cap Interactions	(5) Inv-Mat Interactions
log(capital)	0.098	0.094	0.149	...	...
	(0.005)	(0.021)	(0.010)		
log(materials)	0.571	0.576		0.592	...
	(0.008)	(0.009)		(0.014)	
log(employees)	0.235	0.235	0.204	0.213	0.181
	(0.008)	(0.009)	(0.006)	(0.014)	(0.006)
H workers same Ind	0.073	0.078	0.044	0.094	0.058
	(0.018)	(0.025)	(0.015)	(0.045)	(0.016)
Observations	17937	6892	17937	3063	14120
Adj. R-squared	0.924			0.930	0.948

Dependent variable: Log(Output). Standard errors (in parentheses) clustered by firm. The variable 'H workers same Ind' is the number of workers with HWF experience in the same industry currently observed at non-HWFs. Column 1 reports estimates from the baseline specification. Column 2 implements the procedure in Olley and Pakes (1996). Column 3 implements the procedure in Levinsohn and Petrin (2003). Column 4 adds a third-degree polynomial function of log capital and log investment and the interaction of both functions in t and t+1. Column 5 includes the same controls as col. 5 but replaces log investment with log materials.

Chapter 3

Mobility of Inventors and Innovation

with Sabrina Di Addario

3.1 Introduction

It is widely acknowledged that innovation must be at the heart of long run economic growth. In this Chapter, we investigate the relationship between worker flows and innovative activity. We use a unique dataset that matches administrative employer-employee records to patent data and focus on labor market mobility of inventors. While inventors are not the only workers that may transfer relevant information from one firm to another, they undoubtedly have a large potential to do so.

Specifically, we document the relationship between the hiring of inventors and the innovation output of the firm's employees in three "Third Italy" regions: Veneto, Emilia Romagna and Tuscany.

We estimate an individual - level patent production function that maps the number of workers who have applied for a patent while working at a previous firm and other observed firm characteristics into innovation. This regression equation, which forms the basis of our empirical analysis, is motivated by social interactions theory. The dependent variable in our basic regression is the number of patent applications of each individual employee. The explanatory variable of interest is the number of workers who have applied for a patent while working at a previous firm, constructed from head counts in the matched patent-employer-employee

data. Our preliminary estimates show that the hiring of inventors is positively and statistically significantly related to patenting activity of the firm's other employees. The finding is not driven by unobserved worker or firm permanent heterogeneity. While several robustness checks confirm our results, further analysis is certainly needed. Section 3.5 summarizes the directions for future research.

3.2 Relation to Previous Research

Researchers have discussed the impact of research and development (R&D) on innovation and long run growth. In particular, they have analyzed the role of local R&D spillovers, which have been a major topic in the productivity and industrial organization literatures for several decades.

Studies on game theoretical models of labor mobility as a channel of R&D spillovers, include Cooper (2001) and Gersbach and Schmutzler (2003). The former model examines firms' incentives to undertake research activity in an environment in which employers may move to a rival firm. The latter model endogenizes technological spillovers as a result of decisions made by firms in the market for human capital.

Other theoretical works focus on multinationals' investment in R&D and on the transfer of knowledge across countries. For instance, Markusen (2001) studies the influence of contract enforcement and intellectual property rights protection on the investment of foreign firms into local economies. Also Glass and Saggi (2002) develops a model of inter-firm transfer of technological innovation through the physical movement of workers. Their model has interesting implications that allow studying the incentives of local governments in attracting foreign investments of multinational firms closer to the technological frontier than local firms. Finally, Dasgupta (2011) studies a dynamic general equilibrium model with perfect mobility of workers among countries, in which the long-term dynamic learning process plays a crucial role.

Empirical works looking at the micro-mechanisms behind R&D spillovers is rather limited and indirect.

Some such studies include Bloom, Schankerman and Van Reenen (2007), which develops a methodology that allows identifying the sep-

arate impacts of technology spillovers and product market rivalry effects of R&D. Applying this approach to a panel of U.S. firms, the paper shows that knowledge spillovers quantitatively dominate product market spillovers in the period 1981-2001.

Several empirical studies emphasize the role of R&D in generating positive knowledge spillovers through labor mobility. In particular, Song, Almeida and Wu (2003) shows that labor turnover can facilitate the transfer of knowledge across firms and can explain patterns of patent citations. Rao and Drazin (2002) provides evidence on the role of newly recruited employees on product innovation of young and poorly connected firms. The important role of "learning by hiring" is underlined also by Singh and Agrawal (2011). The authors look at how firms hire inventors to acquire technological competencies and exploit their prior ideas.

Maliranta, Mohnen and Rouvinen (2009) find that firms involved in non-R&D activities hiring workers from R&D-intensive firms tend to perform better, and Tecu (2012) finds that firm hiring an inventor grow 3-5% faster in the following two years. Moreover, Fons-Rosen (2013) finds that foreign direct investment has a greater impact on the host economy in terms of knowledge diffusion when firms reallocate inventors from the already established R&D labs in their home country to the newly developed ones. Intuitively, reallocated inventors have a better knowledge of previous R&D developed by their own (multinational) firm, and might also act as managers of the less experienced local inventors.

Researchers have used data on patents in order to analyze labor mobility and knowledge spillovers. For instance, Moser, Voena and Waldinger (2011) provides evidence that the patenting activity in the U.S. has increased in research fields of German-Jewish refugees after 1933.

The paper most closely related to our study is by Kaiser, Kongsted and Rønde (2011), which shows that mobility of R&D personnel enhances patenting productivity for Danish firms during the period 1999-2004 using a data set that combines patent applications by Danish firms to the European Patent Office (EPO) with matched employer–employee regis-

ter data . Building on this, our econometric framework and our data[1] allow us to refine the identification of the causal effect of firm-to-firm inventor mobility on the patent activity of the individuals in receiving firms. Specifically, we plan to address the main identification issues, namely (a) unobservables correlated with new hires, (b) unobservable worker quality, (c) unobservable firm-level patent productivity shocks at time t+1, using several approaches, as explained below. Moreover, our original survey would allow us to shed light on the micro mechanisms, and on the hiring process[2]. Finally, Third Italy is a very interesting laboratory to investigate the topic of mobility of inventors and innovation for the reasons outlined above.

3.3 Data

This Section describes the dataset and presents descriptive statistics. It draws very heavily on the in-depth description in Depalo and Addario (2013) who use these data to estimate individual returns to patents.

The dataset covers the years 1987-2006 and matches information from two sources: Patstat, the EPO Worldwide Patent Statistical Database, and the administrative dataset of the Italian Security Service INPS (Istituto Nazionale di Previdenza Sociale).

Patstat is a database which provides a detailed description of each patent application, including its title, abstract and technological field, the name and address of residence of all its inventors and applicants (i.e. the firms applying for the patent and retaining the relative property rights), the dates of application, publication and grant. It contains all

[1] Not only do we have information on patenting firms (as in Kaiser, Kongsted and Rønde, 2011), we also have information on the individual inventors. Furthermore, our panel is much longer, which is an important advantage as explained for the different models that we estimate, as explained below.

[2] It is important to emphasize that the answers to the survey would also be important for the econometric analysis using the matched patent-employer-employee data. As we mentioned already, estimating the effect of labor mobility is difficult in the presence of several unobservable variables both at the firm and worker level. The survey will inform on these unobservable variables and allow us to select the most appropriate techniques to deal with them.

patent applications and grants presented at the European Patent Office (EPO) by any Italian firm since 1978, the year in which Italian companies started applying at EPO. We focus on patent applications presented by firm residing in Italy between 1987 and 2006.[3]

INPS is an administrative dataset enabling us to follow private-sector workers and firms over time. It matches employees to employers for the whole period 1987-2006. The information in the INPS dataset at the firm level comprises average gross yearly earnings, average number of employees, industry, municipality of plant location, date of plant opening and plant closure. The information available on employees includes age, gender, municipality of residence and municipality of birth, work status (blue collar, white collar, manager or other), type of contract (full-time versus part-time), length of contract (permanent versus temporary) and gross yearly earnings. We have individual-level information on all the workers employed in any of these firms and the full work history of the employees working for a patenting firm (even if they moved from / to a non-patenting firm).

Since Patstat does not provide VAT codes or other firm identifiers, we do a large matching-name work to link Patstat companies to INPS firms on the basis of the company name and location. Finally, we match the information on inventors from Patstat database to the INPS employees, with the same name and the same employer at the time of the patent application.

Compared with previous work in matching patents to other sources of data at the firm level [4], we can be more precise because we also exploit the information on employees' names and municipality of residence. [5]

The dataset has several attractive features. First, all the co-workers

[3] We exclude patent applications between 1978 and 1986 because for that period we lack the INPS data. We also exclude patents in 2007-2009 because Patstat might be incomplete, due to EPO taking about three years to register all its records. We exclude self-employed and non-formally employed inventors (as well as consultants), and all the applications missing relevant information (e.g. applicant or inventor names, application dates, etc.)

[4] See Thoma et al. (2010) for an extensive discussion on how to combine large datasets on patents at the firm level.

[5] We do the matching at the time of application rather than at the time of grant to maximize the probability that the inventor is still employed in the applicant firm.

of inventors at each point of time are observed in the INPS matched employer-employee data. Moreover, all the mobility events of inventors in all firms are observed. Another interesting feature is that for two regions (Lazio and Veneto) we observe all firms (innovative and non-innovative ones). Finally, the length of the panel covering years 1987-2006 allows to show long enough pre-tend. Figure 3.1 and Table 3.1 present descriptive statistics for the full matched patents-employer-employee. [6] Figure 3.1 (based on Patstat) show that the distribution of total patent applications over the sample period per inventor is very skewed to the left. Table 3.1 shows that patent applications and inventors are mostly concentrated in the manufacturing.

Since some of the empirical models we estimate are computationally intensive we have to restrict our sample. For the analysis below we select all workers with more than 5 observations in the dataset for three "Third Italy" regions: Veneto, Emilia Romagna and Tuscany. Table 3.2 and 3.3 present descriptive statistics for our estimation sample.

3.4 Econometric Framework and Empirical Evidence

Our estimation approach allows the innovation activity of each worker to depend on the number of recently hired inventors in the worker's firm. Specifically, the regression equation that forms the basis of our empirical analysis is:

$$y_{ijst} = \gamma I_{jst} + \beta X_{ist} + \beta_2 Z_{jst} + \mu_{st} + e_{ijst} \tag{3.1}$$

where i indexes the individual, j indexes the firm, s indexed the industry, t indexes time, and y_{ijt} are individual-level patent applications. I_{jst} refers to the number of workers who have applied for a patent while working at a previous firm, and is constructed from head counts in the matched patent-employer-employee data. Other covariates include worker-specific characteristics X_{it} (such as age, age squared, occupation, gender, full-time/part-time status) and firm-specific characteristics Z_{jt} (number of employees in the sample excluding worker i, number of plants)

[6] See Depalo and Addario (2013) for more details.

and industry-year interaction dummies (μ_{st}). [7]As part of a robustness check, we also use a one–period lag.

The presence of firm or worker specific variables that the econometrician does not observe but that affect individual patenting activity may give rise to a bias in the estimated impact of I_{jst}. Of particular concern are both firm-level "permanent differences in appropriability conditions of R&D investments or different technological opportunities" (Kaiser, Kongsted and Rønde, 2011) and individual-level heterogeneity in ability. In order to address these potential endogeneity issues, I estimate models that include individual effects (ψ_i), firm effects $\left(\lambda_{j(i)}\right)$, or both. The baseline linear model with two fixed effects is:

$$y_{ijst} = \gamma I_{jst} + \psi_i + \lambda_{j(i)} + \beta_1 X_{ist} + \beta_2 Z_{jst} + \mu_{st} + e_{ijst} \tag{3.2}$$

Identification of this model is based on variation over time in I_{jst} within a firm for each employee. Even when unobserved worker-specific ability and firm-level heterogeneity are accounted for, estimating the effect of I_{jst} on the innovation output of the firm's workers is difficult in the presence of several other unobservable variables. In section 3.5.1 we describe what type of biases these unobservables may introduce and how we plan to deal with them in the empirical work.

Table 3.4 shows the main estimation results on the sample of three "Third Italy" regions: Veneto, Emilia Romagna and Tuscany. I cluster standard errors (a) at the individual level, and (b) both at the individual and firm level.

Column 1 reports estimates from the baseline OLS specification (Equation 3.1). The coefficient for I_{jst} is positive (0.005) and significant.

Columns 2 and 3 report results using the within-worker and within-firm transformation, while Column 4 reports the results from estimating a linear model with two fixed effects (Equation 3.2). The coefficient for I_{jst} in Column 2-4 is positive and significant.

The point estimates suggest that, on average, recruiting an inventor is related to an increase of 0.003 patent applications made by a given

[7]Poole (2012) estimates a similar equation to study the effect on wages paid in domestic firms in Brazil of the share of new workers previously employed by foreign-owned firms.

worker at firm j. This appears to be a very large effect when compared to the average number of patent applications per year in our sample of workers (0.003). However, the mean I_{jst} is 0.004 and as many as 95 percent of firms in a given year have $I_{jst} = 0$. Hiring one worker of this type therefore implies a very large change for most firms in our data.

In Table 3.5 we lag I_{jst} by one period, since it may take one year for impact to emerge. Results are largely unchanged.

3.5 Future Research

3.5.1 Identification

As mentioned in Section 3.4, even when unobserved worker-specific ability and firm-level heterogeneity are accounted for, estimating the effect of I_{jst} on the innovation output of the firm's workers is difficult in the presence of several other unobservable variables. In this section we describe what type of biases these unobservables may introduce and how we plan to deal with them in the empirical work.

Firm-level unobservables correlated with new hires

A concern is that there exist unobservables correlated with new hires and that these unobservables – rather than knowledge transfer – may account for the measured individual patent activity effects. Our procedure for measuring the number of workers with recent patent applications focuses on newly hired workers. If workers who change firms are more productive than stayers in general, or if the number of recent hires is systematically correlated with time-varying unobservables at the firm level, estimates of the effect of hiring workers with recent patents will overestimate the importance of firm-to-firm inventor mobility for knowledge transfer. In order to address this issue, we augment the regression equation of interest with the number of recently hired workers without previous patent applications. By including both types of new hires (inventors and non-inventors), any potential bias caused by the correlation between unobservables and new hires in general is removed.

Unobservable worker quality

New hires with patenting activity in the past might be on average of higher ability than joiners with no past patenting activity. This selection may upwardly bias our estimates on the effect of joiners with previous patenting activity on the patent activity of stayers. In order to address this issue, we obtain a proxy for worker ability and we weight the number of workers in the regression using this proxy. Specifically, we procure estimates of worker fixed effects from wage equations where both firm and worker effects can be identified (AKM model). We estimate these equations prior to the start of the estimation period for the main analysis (Equation 3.1).

Research and Development Investments

The level of research and development investment is not currently available in our dataset. We plan to obtain it from AIDA (Analisi Informatizzata delle Aziende), a database circulated by Bureau Van Dijk containing official records of all incorporated nonfinancial Italian firms with annual revenues of at least 500,000 Euros.

Patent productivity shocks at time $t+1$

The number of inventors may be correlated with patent productivity shocks happening in the future if inventors can foresee them and apply for jobs in firms with better prospects in terms of growth and/or research conditions. To deal with this threat to identification, we adopt different strategies.

First, we consider an IV strategy based on labor mobility of inventors following closures of R&D labs or large downsizing events. More specifically, we instrument for the number of inventors currently observed at firm j with the number of local inventors in the same industry and locality who were displaced in the previous period. Indeed, following a downsizing event or closure of a R&D lab at an innovative firm, it is more likely that an inventor applies for a job at a local firm because s/he is unemployed and does not want to relocate far away, as opposed to relocating to a particular firm because it offers better prospects. The

IV can be refined in several ways by exploiting the richness of our data. Information on place of residence would allow us to calculate the distance between each inventor's house and the location of the hiring firm. Moreover, in constructing the IV for receiving firm a we could only count inventors who are displaced by firms that rely on the services of the same temporary employment agency as a. [8] Alternatively we could only count inventors who have previously worked with someone at firm a (Cingano and Rosolia, 2013) or have coauthors at firm a.

Further we could address the issue of productivity shocks happening in the future by focusing on events of mobility in which the mobile inventor (a) has not experienced a real wage increase after moving; (b) the real annual wage of the current job is not higher than the average of real wages received in the previous three years; (c) the incomer's wage is not greater than the average wage recorded in the recipient firm and (d) the period of unemployment preceding the start of the new job is more than three months. These conditions are consistent with the inventor being in need of a job and not switching because some firm offers better prospects.

Finally, we could control for current and future R&D investment in a flexible way to proxy for patent productivity improvements happening in the future which inventors may foresee.

3.5.2 Combination of synthetic control methods and event-study techniques

As an alternative empirical strategy, we employ the approach in Severnini (2013)'s paper on hydroelectric damns and agglomeration spillovers, i.e a combination of synthetic control methods (Abadie and Gardeazabal, 2003; and Abadie, Diamond and Hainmueller, 2010) with event-study techniques (Jacobson, LaLonde, and Sullivan, 1993). In this part of the analysis, our estimation is at firm level rather than individual level. The outcome of interest is the total number of firms' patent applications

[8] Gianelle (2011) finds that temporary employment agencies significantly increased the integration and practicability of the inter-firm network of worker mobility in Veneto.

minus the patent applications by the new inventor. An overview of our procedure is as follows. Define a "treated" firm as a firm that hires two of more inventors at time t. Define as control firms, other firms in the same locality and same industry which hire one inventor at time t. First, we use the synthetic control estimator to generate a counterfactual for each treated firm. Each counterfactual, which we refer to as a "synthetic control firm", is a weighted average of the originally defined control firms that reproduces most closely the trajectory of innovation activity that the affected firm would have experienced in the absence of the arrival of the second inventor. We use the following matching variables in the synthethic control estimation: (i) number of patent application up to the year before the arrival of the inventor and (ii) R&D investment up to the year before the arrival of the inventor. Then, we pool all pairs of treated and synthetic control firms, and proceed with our event-study analysis.

3.5.3 An Original Survey

We plan to conduct an original survey in order to shed light on (a) the micro mechanisms behind the improvements in innovation following the hiring of inventors, (b) firm's location choice, (c) the hiring process, and (d) the role of public policies aimed at stimulating research and development (R&D). This is a central component of the project.

One can think of two micro mechanisms to explain the results discussed above. On one hand inventors may share tacit knowledge with their new colleagues thus enhancing the stock of ideas of her new employer. As Tecu (2012) puts it:

> Even though part of an inventor's knowledge is disclosed in patent applications, important aspects of it cannot be codified. If an inventor moves from one firm to another, she takes this tacit knowledge with her.

On the other hand, ideas may have already been present among the worker of a given firm, and inventors are hired to convert the ideas into patentable inventions (Kaiser, Kongsted and Rønde, 2011). In our survey we plan to ask a sample of firms several questions:

- Has your firm benefited from knowledge of inventors from R&D active firms?

- Did the inventor bring with him/her some tacit knowledge thus enhancing the stock of ideas of your firm? Or ideas were already present and the inventor was hired to convert them into patentable inventions?

Questions concerning location choice include:

- When did your firm start production? When did you open your R&D lab (if any)?

- Has the location choice for your production/R&D lab been affected by the presence of the R&D active firms/potential for knowledge spillovers?

Questions concerning the hiring process include:

- Why did the inventors join your firm? Higher wages? Plant closure due to output shocks at R&D active firms/decision to relocate by R&D active firms? Better growth prospects? Job satisfaction rationale?

Questions concerning the role of public policies include:

- How do you finance your R&D expenses? (Banks, venture capital, government funds)

- Which government program(s) did you apply for? Was the application accepted?

- In the absence of the government program(s), how much would you have spent in R&D?

It is important to emphasize that the answers to these questions would also be important for the econometric analysis using the matched employer-employee data. As we mentioned already, estimating the effect of labor mobility is difficult in the presence of several unobservable

variables both at the firm and worker level. The survey will inform on these unobservable variables and allow us to select the most appropriate techniques to deal with them.

3.6 Conclusion

In the first two Chapters of this thesis I have studied issues of labor mobility and agglomeration advantages. Specifically, I identified a set of high-wage firms (HWF) and showed that they are more productive than other firms. Using regression analysis with data for the period 1995-2001, I then showed that hiring a worker with HWF experience increases the productivity of other (non-HWF) firms. In the third Chapter, my coauthor Sabrina Di Addario and I investigated the relationship between worker flows and innovative activity. We used a unique dataset that matches administrative employer-employee records to patent data and focused on labor market mobility of inventors. While inventors are not the only workers that may transfer relevant information from one firm to another, they undoubtedly have a large potential to do so. Our preliminary results show that the number of workers with a previous patent is positively and statistically significantly related to patenting activity of the firm's other employees. As described in detail in Section 3.5 there are several directions that this work could take. For identification of the role of inventors labor market mobility on innovation, further analysis with our unique data is certainly needed. Further, we plan to conduct an original survey in order to shed light on (a) the micro mechanisms, (b) location choice, (c) the hiring process, and (d) the role of public policies aimed at stimulating R&D. These areas are all being actively pursued.

3.7 Figures and Tables

Figure 3.1: *Patent applications per inventor*

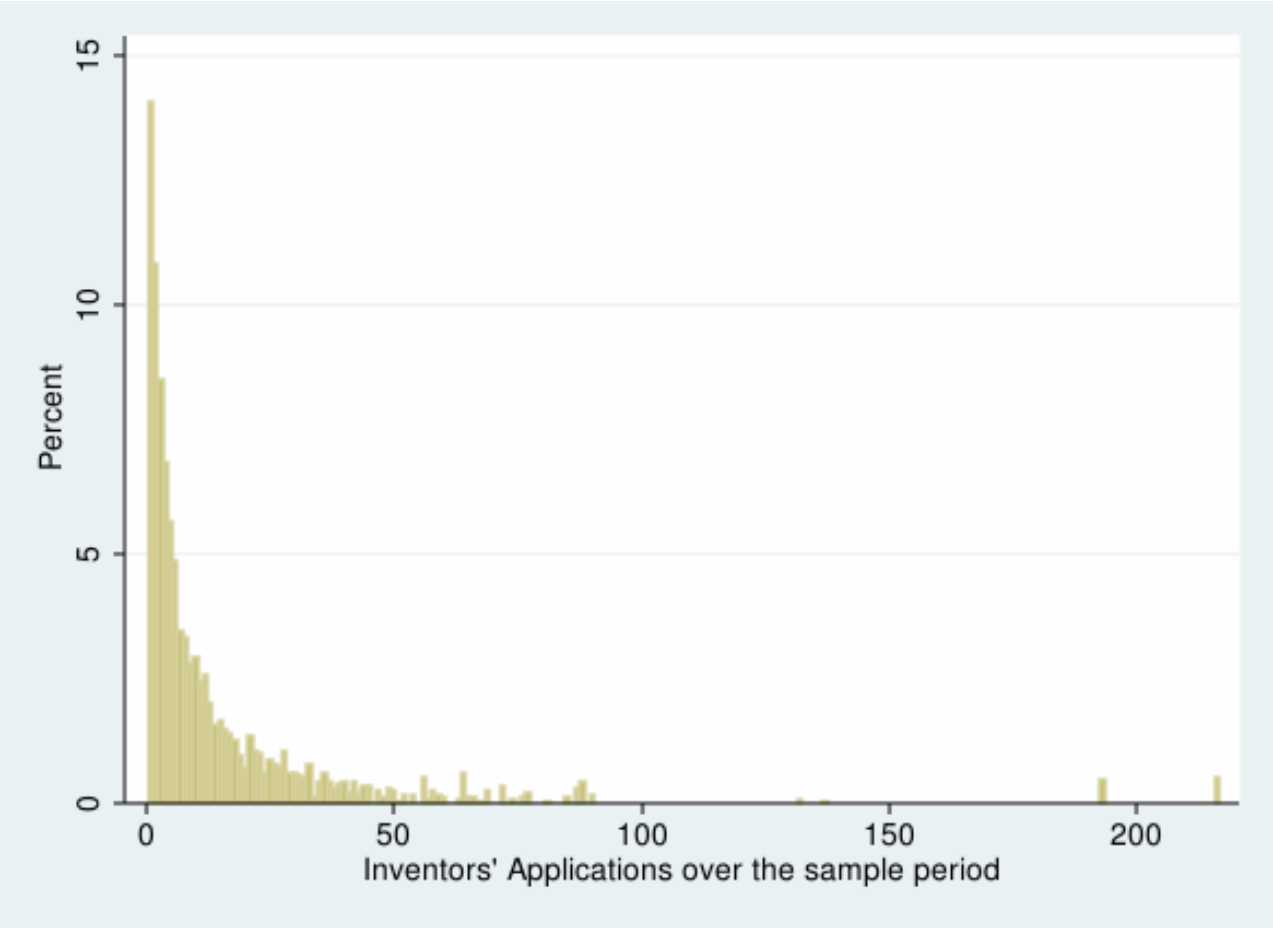


Table 3.1: Distribution of patent applications and inventors by sector

Sector	**Applications**	**Inventors**
Industry	95.8	96.1
Services	0.4	0.2
Public	1.6	2.0
Handcraft	0.3	0.1
Agriculture and Fishing	0.2	0.1
Retail	1.8	1.6

Table 3.2: Estimation Sample: Worker-level Characteristics

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**	**N**
Inventors' appls. per year	0.003	(0.099)	0	30	2493602
Age	39.188	(9.254)	16	64	2493602
female	0.226	(0.418)	0	1	2493602
Fulltime	0.977	(0.151)	0	1	2493602
Blue-collar	0.577	(0.494)	0	1	2493593
White-collar	0.367	(0.482)	0	1	2493593
Manager	0.001	(0.025)	0	1	2493593

Table 3.3: Estimation Sample: Firm-level Characteristics

Variable	**Mean**	**(Std. Dev.)**	**Min.**	**Max.**	**N**
Inventors	0.036	(0.209)	0	2	14745
Employees in sample excluding worker i	168.72	(637.342)	12	21799	14745

Table 3.4: Number of Inventors and Individual Patent Activity

	(1) OLS	(2) Within - Individual	(3) Within - Firm	(4) Twoway
Inventors	0.0054	0.0034	0.0033	0.0033
	(0.0007)	(0.0006)	(0.0007)	(0.0007)
	[0.0025]	[0.0018]		
Observations	2493602	2493602	2493602	2493602
Adj. R-Squared	0.000527	0.319	0.00710	

The dependent variable is the number of individual-level patent applications by worker i. Standard errors in parentheses clustered by worker, in brackets clustered by firm and worker. "Inventors" is the number of workers who have applied for a patent while working at a previous firm. All regressions include worker-specific characteristics (age, age squared, occupation, gender, full-time/part-time status), firm-specific characteristics (number of employees in the sample excluding worker i, number of plants). Sample includes all workers with more than 10 observations in the dataset for the regions of Emilia Romagna, Tuscany and Veneto. Column 1 reports estimates from the baseline specification. Column 2 reports within-individual estimates. Column 3 reports within-firm estimates. Column 4 reports estimates of a linear model with both individual and firm fixed effects

Table 3.5: Number of Inventors and Individual Patent Activity

	(1) OLS	(2) Within - Individual	(3) Within - Firm	(4) Twoway
lag Inventors	0.0051	0.0027	0.0027	0.0024
	(0.0006)	(0.0006)	(0.0006)	(0.0007)
	[0.0024]			
Observations	2286064	2286064	2286064	2286064
Adj. R-Squared	0.000480	0.340	0.00750	

The dependent variable is the number of individual-level patent applications by worker i. Standard errors in parentheses clustered by worker, in brackets clustered by firm and worker. "Lagged Inventors" is the lag number of workers who have applied for a patent while working at a previous firm. All regressions include worker-specific characteristics (age, age squared, occupation, gender, full-time/part-time status), firm-specific characteristics (number of employees in the sample excluding worker i, number of plants). Sample includes all workers with more than 10 observations in the dataset for the regions of Emilia Romagna, Tuscany and Veneto. Column 1 reports estimates from the baseline specification. Column 2 report within-individual estimates. Column 3 report within-firm estimates. Column 4 reports estimates of a linear model with both individual and firm fixed effects

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