Learning-by-Hiring at Entrepreneurial Firms: The Different Contributions of Experienced Inventors to Organizational Knowledge at New Firms

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Abstract: An extensive literature has examined the role of worker mobility for the diffusion of knowledge. For the most part, this literature has focused on large firms. We draw from the literatures on organizational learning, strategy and entrepreneurship to examine different ways in which new firms benefit from hiring experienced workers. We propose the needs of incumbents, in terms of knowledge acquisition, are different from the needs of spinoffs and de-novo entrants: While incumbents hire experience inventors to acquire specific pieces of knowledge, recent entrants hire experienced inventors to build up the firm capabilities. In the case of spinoffs, they also hire many inventors from their parents to obtain knowledge related to the idea that led to the spinoff. Using patent data and detailed information on the origins of merchant semiconductor producers, we analyze how spinoffs and other recent entrants leverage the previous knowledge of the first inventors they hire. Results show that most patenters at new firms have prior patenting experience, while most patenters at incumbents have no prior patents. Hiring inventors from incumbents, and in particular from leading incumbents, increase the probability of entrants using knowledge from other firms. However, in contrast to what happens at incumbents, this knowledge is not necessarily something developed at the mobile workers’ prior employers. We discuss the implications of our findings for understanding how entrepreneurial activity may be affected by policies that aim to restrict worker mobility, and by the availability of knowledgeable mobile workers in industry clusters.

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1. Introduction

Since Arrow (1962) noted that the mobility of employees among firms could be a conduit for the transfer of knowledge, an extensive literature has documented different dimensions of the relationship between worker mobility and knowledge transfer. In knowledge intensive industries, it has been empirically shown that the flow of inventors between firms is followed by flows of information (Singh and Agrawal 2011; Song, Almeida, and Wu 2003). The type and extent of knowledge transfer depends on many factors, including the number of inventors hired from the source firm (Benjamin Aaron Campbell, Saxton, and Banerjee 2014; Groysberg and Lee 2009), the similarity between the source and destination firms (Tzabbar 2009; Argote and Ingram 2000), the litigiousness reputation of the source firm (Agarwal, Ganco, and Ziedonis 2009), among others. In a recent review of the literature on employee mobility, Mawdsley and Somaya (2016) propose that the effect of worker mobility on organizational outcomes can be characterized by the attributes of the mobile employee, source and destination firm, and environmental conditions. They identify the attributes of the source and destination firms as an area that has been understudied. In this study we focus on how startups and incumbents leverage the prior knowledge of inventors they hire, drawing from the literature on capability development to contrast the needs of newer and older firms.

Among entrepreneurial firms, a group that has received significant attention due to the importance of knowledge brought in by their founder are spinoffs (Agarwal et al. 2004; Franco and Filson 2006; Klepper and Sleeper 2005). Spinoffs have been syndicated as key in the development of several industries and regional clusters, including semiconductors, automobiles, tires, and others (Klepper 2010; Buenstorf and Klepper 2010). Evidence also suggest that spinoffs, and in general new firms, benefit from the availability of mobile workers in clusters. For example, Silicon Valley is notoriously famous for its heightened worker mobility (Saxenian 1994), and for the role spinoffs had in the growth of the semiconductor industry in this region (Klepper 2010). During their first few years spinoffs hire many inventors from their parents, but they also hire many experienced inventors from other local firms (Cheyre, Klepper, and Veloso 2014). The literature on spinoffs provide a clear logic for the hiring done from the parent, namely to recruit a base of workers knowledgeable in the idea that led to the spinoff (Agarwal et al. 2004; Klepper and Sleeper 2005). The contribution of inventors hired from other unrelated local firms is less obvious.

The learning-by-hiring literature would suggest that a main motivation for this hiring is the prospect of acquiring firm-specific knowledge from the inventors’ previous employers (Song, Almeida, and Wu 2003). Nonetheless, this literature has mostly focused in the exchange of inventors between established firms and may be ill suited to explain how recent entrants leverage the experience of their initial hires. The motivations usually named to justify the need of incorporating external knowledge, such as breaking path-dependencies (Nelson and Winter
1982), or balancing exploration of external knowledge vs. exploitation of internal ideas (March 1991), are problems that affect incumbents rather than new firms. Instead, entrepreneurial firms lack direct experience and are constrained in resources and capabilities. To develop the capabilities they lack, new firms may resort to hire knowledgeable workers from incumbents (Fahrenkopf and Argote 2015).

This paper seeks to clarify how inventors hired from different sources contribute to new ventures. We argue that acquiring firm specific knowledge from an inventor’s previous employer is not the main concern of recent entrants. While firms that lack a defined technical trajectory may be more likely to hire inventors with the objective of accessing their previous employers’ knowledge (Song, Almeida, and Wu 2003), they first need to develop the capabilities necessary to assimilate this knowledge. The capacity of a firm to acquire knowledge from external sources is limited by its experience (Nelson and Winter 1982), and its ability to capture knowledge spillovers depends on its internal stock of knowledge (Cohen and Levinthal 1990). We hypothesize that young entrants may overcome their initial lack of experience and absorptive capacity by hiring experienced workers from different firms in the industry. In this context, many of the inventors hired by new firms will help build these firms’ capabilities. The specific knowledge necessary to develop the idea that led to the spinoff will be provided by the founder, and by other inventors recruited by him among his former co-workers.

To test this theory, we follow a large literature on knowledge diffusion and use patent citations to infer knowledge flows. The distinguishing feature of this work is that we note that the mobility of workers results in the acquisition of different types of knowledge. When an inventor is hired away by a competitor, all of the knowledge the inventor possesses gets transferred to the new organization. Part of this expertise will be firm specific. This corresponds to skills, knowledge or routines that are particular to his previous employer. The inventor acquired this knowledge by solving particular problems that his previous employer faced (March and Olsen 1975; Levitt and March 1988). We interpret an increase in citations to patents assigned to the mobile inventor’s previous employer as a proxy for the acquisition of firm specific knowledge. The mobile inventor also possesses knowledge that is not specific to his prior employer, but instead are industry specific skills that are applicable to many firms in the same industry (Neal 1995; Castanias and Helfat 1991, 2001). We use increases in citations to patents assigned to firms other than the inventor’s previous employer as a proxy for the acquisition of industry specific knowledge.

Results are consistent with the idea that the hiring of experienced inventors results in the acquisition of firm specific knowledge, as well as industry specific knowledge. In the case of recent entrants, the acquisition of firm specific knowledge is only significant when the inventor is hired from the parent. Experienced inventors make a strong contribution in terms of industry specific knowledge when hired by young firms, but this contribution is negligible when they join incumbents. We perform several robustness checks and try alternative models in order to rule
out alternative explanations. We first check that our results are not driven by the growth of firms rather than from hiring of experienced inventors. We do a placebo test to verify that the increase in citations occurs after the inventors are hired. Finally, we employ fixed effects to control for unobserved characteristics of the cited firms or for unobserved relations between the cited and the citing firms.

This paper contributes to the entrepreneurship and learning literatures. We complement prior work on spinoffs (Agarwal et al. 2004; Klepper and Thompson 2010; Figueiredo, Guimarães, and Woodward 2002) by extending our understanding on how founders put together the expertise necessary to start their ventures. This also contributes to a recent body of work that examine the contribution of the founding teams of new ventures (Agarwal et al. 2013; Campbell et al. 2011). This paper also extends prior research on learning (March and Olsen 1975; Levitt and March 1988; Argote, McEvily, and Reagans 2003) by identifying how knowledge acquired through previous employment is deployed in new ventures. Analyzing the results with a broader perspective also sheds some lights on the economics of agglomeration economies. It has long been established that firms located in clusters enjoy a series of benefits that arise from agglomeration economies (Rosenthal and Strange 2004). Our findings suggest that the contribution of inventors hired by spinoffs from firms other than the parent is fairly generic. This helps in understanding why spinoffs out of clusters locate close to the parent, even when there exists a cluster in another region. Re-locating in a cluster would make easier to access industry specific knowledge, but staying close to the parent allows spinoffs to benefit from the pre-entry knowledge of their founder (Buenstorf and Klepper 2010; Figueiredo, Guimarães, and Woodward 2002), which is conceivable more unique and difficult to obtain.

2. Theory and Hypotheses

The learning-by-hiring literature portrays the acquisition of knowledge through hiring experienced inventors as a strategic action that makes more sense for established firms than for recent entrants (Song, Almeida, and Wu 2003; Singh and Agrawal 2011; Rosenkopf and Almeida 2003). The usual account says that as firms develop significant internal resources, the generation of ideas becomes path dependent (Nelson and Winter 1982). In order to innovate more effectively, firms benefit from integrating external knowledge by achieving a better balance between the exploitation of internal ideas and the exploration of external knowledge (March 1981). The most valuable knowledge is also the most difficult to integrate into the firm. It is often tacit and thus highly embodied in the organization (Kogut and Zander 1992). In this context, hiring mobile inventors is a good strategy for acquiring distant and complex knowledge.

This reasoning assumes that a prime motivation to hire a mobile inventor is the acquisition of specific and valuable knowledge that is distant to the firm. Empirical evidence supports this assumption. In a study of outbound employee mobility from IBM, Palomeras and
Melero (2010) find that IBM’s inventors who are more likely to get hired away by other firms are those with better quality patents, whose knowledge is not interdependent with other inventors at the firm and whose expertise is in areas where IBM is a technological leader. Studies that look at how the knowledge of mobile inventors is integrated at the receiving firm find that mobile inventors cite their previous patents at the new firm, and that this knowledge disseminates primarily through their new network of collaborators, who also start citing previous patents of the mobile inventor more frequently (Singh and Agrawal 2011). Other studies find that not only the knowledge of the inventor gets transferred. Other patents of the source firm also get cited more frequently after the inventor moves (Song, Almeida, and Wu 2003; Rosenkopf and Almeida 2003), even in cases where the prior firm has exited the market (Hoetker and Agarwal 2007).

The results presented above describe firm specific knowledge that the mobile inventor acquired through previous employment. Nevertheless, the contribution of mobile inventors is not limited to knowledge that was created at their previous employer. The ability of a firm to integrate knowledge that was generated at other organizations depends on its “absorptive capacity” (Cohen and Levinthal 1990). In its original conceptualization, this capability is related to investments in R&D in fields related to what the firms want to learn. Lim (2009) proposes that there are different types of absorptive capacities that allow firms to capture different types of knowledge. One of the mechanisms to boost the firm’s ability to capture disciplinary knowledge (which in our terminology would correspond to industry specific knowledge) is hiring discipline-trained workers. For young firms, this provide an accelerated way of acquiring absorptive capacity, compared to developing this capability by investing in lengthy R&D projects. We propose that mobile inventors contribute to a firm’s absorptive capacity with the knowledge they have acquired throughout their career. This is not necessarily knowledge that was generated at the inventor’s previous employer. Instead, it is all the body of knowledge the inventor must master to conduct his research. In what follows we analyze how incumbents, recent entrants, and spinoffs differ in their needs for industry specific and firm specific knowledge.

2.1 Incumbents

The literature has mostly focused on the acquisition of firm specific knowledge from inventors’ previous employers by looking at flows of inventors between incumbents. Studies using varied methodologies consistently find that when an inventor changes employers, knowledge gets transferred from the source to the destination firm (Singh and Agrawal 2011; Song, Almeida, and Wu 2003; Rosenkopf and Almeida 2003). The amount of knowledge transferred and the effect on the receiving firm changes according to the receiving firm’s characteristics and the activity the inventor pursues at the new firm. The transfer of knowledge seems to be more effective when the inventor brings knowledge that is new to the organization
and when the receiving firm is not overly reliant in their own internal knowledge when developing new innovations (Song, Almeida, and Wu 2003). Hiring inventors with distant knowledge increases the chances of the firm repositioning on the technological space, with the greater effect happening when the distance between the receiving firm and the inventor’s knowledge is moderate (Tzabbar 2009). This leads to a first hypothesis about firm specific learning at incumbents, which is in line with previous works:

**Hypothesis 1a:** When incumbents hire experienced inventors, they do so mainly to acquire firm specific knowledge from the inventors’ previous employers. As incumbents will most likely have well-developed internal capabilities, their need to develop their absorptive capacity by hiring experienced inventors should be limited. While hiring experienced inventors will also result in the acquisition of industry specific knowledge, this is not the main objective for incumbents. The industry specific knowledge mobile inventors bring in is more likely to be redundant when the hiring firm is an incumbent.

**Hypothesis 1b:** For incumbents, the acquisition of additional industry specific knowledge can be considered a by-product of hiring an inventor and is thus of lesser importance.

### 2.2 Recent Entrants

We have argued that established firms hire experienced inventors mostly to gain access to the inventor’s previous employer’s knowledge. The motivation of incumbents is integrating diverse knowledge and breaking path dependencies. We expect this to work differently at recent entrants. New firms are narrowly focused and produce innovations in fields not crowded by incumbents (Almeida and Kogut 1997). Thus, they should be less interested in integrating diverse knowledge generated by competitors. They do not need to break path dependencies, as they have no prior history. For the most part, the main reasons that moved incumbents to hire experience inventors do not apply to new firms.

Instead, recent entrants are more interested in acquiring industry specific knowledge. The limited research history of new organizations limit their ability to internalize knowledge generated at other organizations. To overcome this limitation new organizations may resort to hiring experienced inventors (Lim 2009). In doing so, they are not interested in obtaining specific pieces of information. Instead, they are looking for the general abilities of the inventor. The greater effect will be realized with inventors hired from a leading firm, as these should have acquired more and better knowledge through their employment.

**Hypothesis 2a:** Movement of inventors from incumbents to unrelated recent entrants will be associated with low levels of acquisition of firm specific knowledge from the inventor’s previous employer.

**Hypothesis 2b:** Movement of inventors from incumbents to unrelated recent entrants will be associated with high levels of acquisition of industry specific knowledge.
2.3 Spinoffs

Not all new firms are the same. A type of entrant that is of particular relevance when considering the role of inventor mobility is spinoffs. The creation of a spinoff has at its core the movement of an employee to establish the firm. Thus, one would expect this to be relevant when considering inventor mobility. Moreover, most of the entrants in the semiconductor industry, which motivates this study, were spinoffs and eventually these were also nearly all of the industry leaders (Klepper 2010).

The transfer of knowledge from parents to spinoffs is at the center of the creation of these firms. Employees might acquire technical and market related know-how at incumbents and decide to form their own firms to compete with their former employers (Agarwal et al. 2004; Franco and Filson 2006; Chatterji 2009). Still, while spinoffs inherit technical knowledge from their parents, they often pursue a different idea, which may not have been valuable to the parent (Klepper and Sleeper 2005) or whose value was misjudged by it (Klepper and Thompson 2010). In the semiconductor industry, disagreements about the value of inventions and on the course the firm should follow were prevalent (Klepper and Thompson 2010). This resulted in many influential inventions being made at incumbents and developed at spinoffs. During their first years spinoffs draw many inventors from their parents to staff their initial endeavors (Cheyre, Klepper, and Veloso 2013). We hypothesize that this increased hiring from the parents is not only because it is easier for the founder to recruit former co-workers, but is also the result of a deliberate strategy to draw from the parent’s knowledge. Not only will spinoffs hire more inventors from the parent, but also each of these inventors will bring in more knowledge than inventors that come from other firms.

Hypothesis 3a: Movements of inventors from parents to spinoffs will result in a greater transfer of firm specific knowledge than movements between other types of firms.

As the main objective of hiring inventors from the parent is to tap into the parent’s knowledge we do not expect this hiring to have an important effect on the acquisition of industry specific knowledge.

Hypothesis 3b: Movements of inventors from parents to spinoffs will not be related with a significant acquisition of industry specific knowledge.

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1 This is not a phenomenon unique to the semiconductor industry; this is also the case in the tires (Buenstorf and Klepper 2010), hard disk drives (Franco and Filson 2006; Agarwal et al. 2004), and several other industries.
3. Data

The aim of our hypotheses is to determine how a firm’s heritage and tenure affect how it leverages the previous experience of the inventors it hires. Testing these hypotheses requires data on the mobility of inventors, on the transfer of knowledge between different firms, and, more importantly, on the heritage of semiconductor producers. Data on inventor mobility and knowledge flows can be readily inferred from patent filings. Obtaining information on firms’ heritage, which is a distinguishing feature of our analysis, is particularly difficult. It requires determining the date of entry of all producers, who the founders were, and what they were doing before.

Klepper (2009) compiles the heritage of 101 major merchant semiconductor producers that enter through 1986. To produce this data he used several sources, of which the most important were the Silicon Valley Genealogy and information compiled by the consulting firm “Integrated Circuit Engineering” (ICE) on annual sales from 1974 to 2002 of the largest semiconductor firms. The Silicon Valley Genealogy is a resource compiled by the trade association Semiconductor Equipment and Materials. For all the semiconductor firms that entered in Silicon Valley through 1986, it lists who the founders were and where they previously worked. We supplement Klepper’s (2009) data with information on four additional firms that are listed in the ICE sales data and that entered in 1987.

We download all patents granted between 1970 and 2002 in five main semiconductor classes from the USPTO website. To determine which of these patents belonged to ICE firms, we used the firm identifiers in the 2004 update of the NBER patent database (Hall, Jaffe, and Trajtenberg 2001). We focus on semiconductor patents in order to identify inventors with knowledge relevant to semiconductor entrants. While the five classes capture around 60% to 70% of patents issued to Silicon Valley producers on our list, it only identifies about a third of the patents of diversified firms located outside of Silicon Valley, such as RCA, TI, and Motorola. Adding inventors who worked at firms with a semiconductor division, but who didn’t have semiconductor patents themselves, would produce unwanted heterogeneity on the utility of the inventor’s knowledge for recent entrants. Analyzing mobile inventors with similar expertise gives us confidence that the variations observed are due to differences in the source and hiring firms’ backgrounds and not to disparities in the value of the inventor’s previous knowledge to the firm.

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2 All firms whose annual sales exceed a certain threshold are included in the compilation.

3 Founder is defined as someone who organizes the firm and initially works at it.

4 The classes included: 257 (Active Solid-State Devices), 326 (Electronic Digital Logic Circuitry), 327 (Miscellaneous Active Electrical Nonlinear Devices, Circuits, and Systems), 365 (Static Information Storage and Retrieval), and 438 (Semiconductor Device Manufacturing).
In order to identify all patents of an inventor, we rely on the inventor identifiers from Lai, D'Amour, and Fleming (2009). As this only covers patents granted after 1975, for earlier patents the classification was done manually by sorting the patents by inventor name and checking for subtle differences in the way some inventors’ names were recorded. Extending this manual verification to patents granted beyond 1976, we also adjusted the classification for a small number of inventors.

In order to infer changes of employer, each inventor’s patents were ordered by time of application. For explanatory purposes, let us denote two consecutive patent applications by the same inventor as $A_1$ and $B_2$, where the subscript denotes the application date of the patent, and $A$ and $B$ denote the assignee of each patent. We consider that a change of employer occurred if firms $A$ and $B$ are different, with a couple of exceptions. If firm $B$ acquired firm $A$ in the year before date 2, we considered that no job change occurred as the first patent now belongs to firm $B$. There were a number of cases where we found inventors with sequences of consecutive patents of the form “$A_1A_2B_3A_4B_5B_6$”. Patent $A_4$ was likely applied for the inventor by firm $A$ after he had moved to firm $B$. In these cases, we consider that the inventor moved from firm $A$ to firm $B$ sometime in between dates 3 and 4. Finally, we only consider changes of employer where the inventor moved directly from firm $A$ to firm $B$. In order to implement this, we checked for patents granted to the inventor between time 1 and time 2 at any firm on any class, and excluded all movements where we found a third employer in between.

When inferring changes in employment from patent data, it is difficult to estimate the date when the change actually happens. It is reasonable to assume that when two consecutive patents ($A_1B_2$) have different assignees, the inventor changed employers at some time between dates 1 and 2. Nonetheless, after reconstructing the work history of 13 randomly selected moving inventors, we found that in several cases they moved before date 1. Analyzing the time between patents of moving inventors versus inventors that stay at the same firm helps on establishing a rule to date changes in employment. For stayers, the average time between consecutive patents is 1.7 years, while for movers it is 6.2 years. The difference could be due to many causes, including that the moving inventor needs some time to get established at the new

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5 A later revision of the database we used, published by Lai et al. (2011), contains a more accurate disambiguation of inventor names. This version was released after we had already manually cleaned up our database.

6 There were also a small number of cases where we observed sequences of the form “AABAAA”. In these cases we considered that the patent was the result of co-invention with inventors of firm $B$ that ended up being assigned to firm $B$. In these cases we consider no movement occurred.

7 To implement this we obtain all patents granted to each inventor in our sample from Lai et al. (2009) and check if between patents that correspond to a change of employer there are interim patents at other firms. This only provides information on patents granted from 1976, and thus we cannot rule out that movements that occur prior to 1976 are direct. Comparing with post 1976 figures reveals this does not seem to be a problem.
firm or adopts a managerial role at the new organization. The date we assign to the inventor movement has important consequences for the analysis. Given that our aim is to find increases in citations after the movement happens, the most conservative strategy is to err on the side of dating the movement too early. Consequently, we date the year of the move based on date 1 with two exceptions. If the inventor applied for a non-semiconductor patent at firm A after date 1, we use the date of his latest patent at firm A. If firm B entered later than date 1, we use the year of entry of firm B as the date of the movement.

The resulting sample has a total of 11,774 patents applied for on or before 1987 by 4,880 inventors. Of the 105 firms initially identified, 86 were granted patents. The earliest application year is 1961, but patents applied before 1967 are scarce. The time covered by the dataset allows us to have a sizable number of patents when major players of the industry were entering in Silicon Valley. When identifying movements, we consider only movements that happen up to 1987, because this is when our information on the origins of firms ends. While the movements are restricted to those that happened before 1987, i.e. the patent at the original firm must be applied on or before 1987, we allow the patent at the new firm to be granted up to 2002 in order to permit sufficient time to elapse to detect a change in employer. Out of the 4,880 inventors with patents applied on or before 1987, 2,508 had at least two patents. Of these inventors, 279 moved once, 27 moved twice, and one moved three times.

Finally, we also need information on patent citations, which is challenging to obtain for patents granted before 1976. Each patent filing contains citations to the knowledge upon which the invention builds on. But, we are not interested in the citations made by a patent; instead we are interested in the citations received by a patent. In order to produce this information, even for a single patent, it is necessary to collect all citations made by every patent granted after that patent’s application date. This information is only available in electronic form for patents granted from 1976. The NBER patent database project (Hall, Jaffe, and Trajtenberg 2001) compiled a database of pairwise citations with the information available from the USPTO. We use this dataset for patents applied from 1976\(^8\). For earlier patents we supplemented this dataset in two ways. First, we collect citations made by all patents of ICE firms granted between 1970 and 1975 when the information was available in a machine readable form from the USPTO website. Then, we searched for all patents that cite IC patents of ICE firms using the website ip.com. This website provides a free intellectual property library that supplements its data with

\[\text{footnote}{8}\] The original NBER patent citation database released in 2001 contained all citations made by patents granted from 1976. Citations received by patents granted before 1976 were truncated, as citations made by patents granted before 1976 weren’t included. The latest update of the NBER patent citation database only contains citations made by patents granted from 1976 to patents granted from 1976, excluding in this way the patents that suffered from this type of truncation.
information from the DOCDB\(^9\) database of the European Patent Office when the information is not available in electronic form from the USPTO. While we are careful in retrieving as much information as possible for pre-1976 patents, it is still possible that the data is truncated for a small number of patents. After supplementing the database of pairwise citations, we use the firm identifiers in the 2004 update of the NBER database (Hall, Jaffe, and Trajtenberg 2001) to identify the assignees of the citing patents.

4. Statistical Analysis

4.1 Hiring Patterns

If spinoffs, other startups, and incumbents have different uses for inventors’ previous experience, this ought to relate to the background of the inventors hired by each of these firms. In table 2 we compare the background of inventors that patent for the first time at an assignee, distinguishing between incumbents and recent entrants. For operational purposes we define recent entrants as firms that are 5 years old or younger\(^10\) and consider all other firms as incumbents. Inventors are classified as “Mobile” if they have prior patents with a different employer or as “New” if the patent at the firm is their first patent. Column Hired is the sum of New and Mobile and corresponds to the number of inventors who patent for the first time at the firm in the different time periods.

<table>
<thead>
<tr>
<th>Year Range</th>
<th>Recent entrants (5 yrs or younger)</th>
<th>Incumbents (Older than 5 yrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hired</td>
<td>New</td>
</tr>
<tr>
<td>1971 to 1975</td>
<td>52</td>
<td>27</td>
</tr>
<tr>
<td>1976 to 1980</td>
<td>20</td>
<td>6</td>
</tr>
<tr>
<td>1981 to 1985</td>
<td>83</td>
<td>27</td>
</tr>
<tr>
<td>After 1985</td>
<td>66</td>
<td>30</td>
</tr>
<tr>
<td>Total</td>
<td>221</td>
<td>90</td>
</tr>
</tbody>
</table>

Table 2 shows that incumbents hire almost exclusively inventors who have never patented before. In contrast, recent entrants heavily rely on inventors with prior experience. This suggests that incumbents see little benefit in hiring experienced inventors or that recent

\(9\) DOCDB is the master documentation database from the European Patent Office. It has worldwide coverage and contains bibliographic data, abstract, and citations. Bibliographic data is available from 1920 for some patent authorities. See http://www.epo.org/searching/subscription/raw/product-14-7.html

\(10\) This choice is an arbitrary threshold. We experimented using a larger threshold and found that enlarging the period where firms are considered recent entrants does not add many movements from other firms.
entrants disproportionately need experienced inventors to build up their capabilities. We now turn to analyzing how incumbents and recent entrants leverage the experience of the group of inventors hired from other firms.

4.2 Tracing Knowledge Flows

We follow an extensive tradition of works that use patent citations as a proxy for knowledge flows\(^\text{11}\). The usual practice consists on comparing citations made to a patent of interest with citations made to a comparable control patent. In our case this corresponds to comparing, during the post-move period, the number of citation made by the hiring firm to previous patents of the moving inventor with citations made to a similar patent of a different firm. As explained by Singh and Agrawal (2011), a drawback of this methodology is that it ignores potential unobservable differences between the inventors of the focal and control patents and fails to account for the effect of a potential shift of the hiring firm’s strategy. Even with careful selection of the control group, the moving inventor’s patents can be more valuable to the hiring firm. If this was the case, there would be more citations to the moving inventor’s patents even if he had not been hired. Moreover, the hiring decision could be the result of a shift of the firm’s strategy, and thus not all of the increase in citations can be attributed to learning that results from hiring. Singh and Agrawal (2011) deal with this issue by using a difference-in-difference approach and by using patent fixed effects in their regression analysis. Unfortunately this strategy is not feasible in our setting. Their identification strategy is based on differences in citation rates between the pre-move and the post-move period. As we are interested in studying the very first hires of a firm, there is no pre-move period.

To explain the effect of hiring on knowledge acquisition, we implement citation counts models between dyads of firms. The idea is to explain knowledge flows between a pair of firms during a time period as a function of inventor flows in previous time periods. This framework allows us to leverage the longitudinal nature of the data, and by adding fixed-effects, we can ameliorate some of the concerns related to the relationship between hiring an inventor from a given firm and the value of his knowledge to the hiring firm. Our methodology is akin to previous works on knowledge flows resulting from inventor mobility (Rosenkopf and Almeida 2003; Oettl and Agrawal 2008; Almeida, Dokko, and Rosenkopf 2003). The main variation we introduce is measuring how hiring experienced inventors can help in acquiring knowledge from firms other than their previous employers. Figure 1 explains the novelty of our analysis in analyzing the flow of knowledge between a citing (hiring) and a cited (source) firm. Previous studies have centered on how the hiring of inventors by the citing firm can lead to an increase

\(^{11}\) The work of Jaffe et al. (1993) on the geographical localization of patent citations started this tradition. Works that specifically address the relationship between inventor mobility and knowledge transfer include Song et al. (2003), Rosenkopf & Almeida (2003), Almeida et al. (2003), Agrawal et al. (2006), among others.
in citations from the citing to the cited firm\textsuperscript{12}. We propose this corresponds to a measure of the acquisition of \textit{firm-specific} knowledge. We introduce new variables to measure how the hiring of inventors by the citing firm from any other firm (i.e., not from the cited firm) can lead to an increase in citations to patents of the cited firm. We propose this is a proxy for the acquisition of \textit{industry-specific} knowledge. The citing firm is acquiring expertise in inventions developed by the citing firm indirectly by hiring inventors from other firms. Conceivably, as industry specific knowledge has diffused throughout the industry, these inventors acquired this knowledge vicariously through past employment.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Measuring acquisition of firm specific knowledge (left side) and of industry specific knowledge (right side).}
\end{figure}

Citation counts between dyads of firms are highly skewed. In most cases there will be zero citations between firms in a dyad, and in a few cases there will be a sizable number of citations. Thus, as the dependent variable is overdispersed, we use negative binomial regressions. To construct the sample, we form all pairwise combinations between ICE firms with at least one patent and create one observation per dyad for each year from 1967 to 1987. Dyad-years where one of the firms had not yet entered or had already exited the market are dropped. Calling one of the firms in the dyad “citing firm” and the other “cited firm”, the dependent variable $\text{Citations}_t$ is defined as the number of citations made by patents of the citing firm filed in time $t$ to patents of the cited firm.

The main explanatory variables are the number of inventors hired by the citing firm from the cited firm in the last five years counted from the date of the observation, and an analogous variable counting the number of inventors hired by the citing firm from all other firms. Additionally, we specify several interactions to isolate the effect of inventors hired while the firm was a recent entrant, of inventors hired from the parent, and of inventors hired from the leading firms. These variables are explained in detail as we introduce the models. The Appendix provides a summary table and some descriptive statistics.

\textsuperscript{12} Not all previous works analyze knowledge flows between dyads of firms. Oettl and Agrawal (2008) analyze knowledge flows between source firm and destination country.
We also include several control variables to take into account the size of the firm and its ability to learn from competitors. In order to control for the ability of the firm to recognize and incorporate external knowledge, i.e. its absorptive capacity (Cohen and Levinthal 1990), we include the log of its stock of IC patents. We define the stock of IC patents as the number of patents filed by the firm, in any of the 5 main IC patent classes, since the beginning of the sample. Firms with a larger stock of patents have greater absorptive capacity and thus a higher likelihood of citing patents of other firms (Cohen and Levinthal 1990). We also include the log of the stock of IC patents of the cited firm, as firms with a larger stock of patents are more likely to get cited. We also control for the number of patents filed by the citing firm in the year of the observation, as this is directly related to the number of citations made by the firm during the year. Finally, we add a dummy that is equal to one if the citing and the cited firm are located in SV and a dummy that indicates if they are located in the same region outside of SV.

In the first model, we introduce the two hiring count variables, along with all controls. Coefficient estimates are presented in Table 3. The “# inventors hired from cited” variable measures the number of inventors hired by the citing firm from the cited firm in the last 5 years from the date of the observation. The “# inventors hired from others” variable counts the number of inventors hired from firms other than the cited firm in the same time period. The coefficient estimates of both variables are positive and significant. In negative binomial models the coefficient estimates can be readily interpreted as the semi-elasticity\(^\text{13}\). Thus, each additional inventor hired is associated with a 32% increase in citations to patents of the inventor’s previous employer, and with a 5% increase in citations to patents of each of all other firms. While the “per inventor” effect of the # inventors hired from others variable is much smaller than the effect of the # inventors hired from cited variable, bear in mind that # inventors hired from others aggregates hiring from several firms. The coefficients of the control variables conform to our expectations.

The coefficients of both local dummies are positive, although only the coefficient corresponding to SV is significant. They imply that even after controlling for inventor mobility, citations to co-located firm are 62% greater than citations to non co-located firm in the case of SV and 27% greater in the case of other regions. This suggests that inventor mobility is not the only conduit for the local diffusion of knowledge\(^\text{14}\) and other mechanisms are in place. Overall, model 1 supports the idea that hiring an experienced inventor results in the acquisition of firm specific knowledge from the inventor’s previous employer, as well as of industry specific

\(^{13}\) This means that a 1 unit change in the independent variable is associated with a percent change equivalent to \(\exp(B)-1\).

\(^{14}\) If we estimate model 1 without the hiring count variables, the coefficients of local SV and local nSV are larger, 0.637 and 0.258 respectively.
knowledge. In subsequent models we introduce a series of interactions to understand better which type of firms the most from each kind of learning.

Table 3: Coefficient estimates for negative binomial models of non-self citations between dyads of firms.

|                                 | Model 1       | Model 2       | Model 3       | Model 4       |
|                                 | 0.279***      | 0.223***      | 0.366***      | 0.367***      |
| # Inventors hired from cited    | (0.076)       | (0.052)       | (0.081)       | (0.082)       |
| # Inventors hired from others   | 0.047***      | 0.041**       | 0.007         | 0.008         |
|                                 | (0.015)       | (0.016)       | (0.020)       | (0.020)       |
| Initial hiring from cited * spinoff | 0.479**      | 0.351*        | 0.146         |               |
|                                 | (0.205)       | (0.203)       | (0.212)       |               |
| Initial hiring from others * spinoff | 0.032        | -0.002        | -0.068        |               |
|                                 | (0.125)       | (0.129)       | (0.109)       |               |
| Initial hiring from cited * (1-spinoff) | -0.113     | -0.089        | -0.084        |               |
|                                 | (0.128)       | (0.115)       | (0.116)       |               |
| Initial hiring from others * (1-spinoff) | 0.081*      | 0.090*        | 0.093*        |               |
|                                 | (0.044)       | (0.047)       | (0.047)       |               |
| Log (Stock IC patents cited firm) | 0.950***      | 0.955***      | 0.962***      | 0.961***      |
|                                 | (0.020)       | (0.019)       | (0.020)       | (0.020)       |
| Log (Stock IC patents citing firm) | 0.710***      | 0.741***      | 0.738***      | 0.742***      |
|                                 | (0.054)       | (0.059)       | (0.059)       | (0.059)       |
| Nr. Patents citing firm        | 0.007**       | 0.006**       | 0.006**       | 0.005**       |
|                                 | (0.003)       | (0.003)       | (0.003)       | (0.003)       |
| Local not SV                   | 0.238         | 0.189         | 0.188         | 0.163         |
|                                 | (0.145)       | (0.140)       | (0.138)       | (0.141)       |
| Local SV                       | 0.485***      | 0.471***      | 0.480***      | 0.457***      |
|                                 | (0.118)       | (0.115)       | (0.124)       | (0.123)       |
| # Inv. Hired from cited * leader | -0.175        | -0.179        |               |               |
|                                 | (0.121)       | (0.123)       |               |               |
| # Inv. Hired from leaders       | 0.082**       | 0.080**       |               |               |
|                                 | (0.040)       | (0.040)       |               |               |
| Recent spinoff (10 years)       |               |               |               | 0.724*        |
|                                 |               |               |               | (0.371)       |
|                                 | (0.211)       | (0.217)       | (0.215)       | (0.217)       |
| Observations                   | 49243         | 49243         | 49243         | 49243         |

*** p<0.01, ** p<0.05, * p<0.1    Robust standard errors in parentheses

In model 2 we introduce two additional hiring count variables. “Initial hiring from cited” counts the number of inventors that the citing firm hired from the cited firm, but only considering the hiring that occurs while the citing firm is a recent entrant (5 years old or
"Initial hiring from others" is analogous for inventors hired from firms other than the cited firm. As in the other hiring variables, these consider movements that happened in the last five years. These variables are also introduced interacted with a “spinoff” dummy, which is equal to 1 if the citing firm is a spinoff of the cited firm. This allows us to distinguish the effect of hiring inventors from the parent or from other firms.

The interaction Initial hiring from cited * spinoff counts the number of inventors hired from the parent while the spinoff was young. Note the effect is additive to that of the # inventors hired from cited variable. The coefficient is positive and significant, indicating that each inventor hired from the parent increases citations to patents of the parent by about 102%. The Initial hiring from others * spinoff interaction measures how inventors hired from firms other than the parent, while the firm was young, contribute to acquiring knowledge from the parent. The coefficient is not significant, which indicates that inventors hired from other firms have no additional effect on acquiring knowledge from the parent. Both these coefficients are consistent with hypotheses 2a and 2b.

To measure the effect of initial hiring from firms other than the parent we interact Initial hires from cited with (1-spinoff). As before, the effect of this interaction is additive to # inventors hired from cited. The coefficient estimate is negative and insignificant, which implies that, if anything, the acquisition of firm specific knowledge is less important when the hiring firm is a recent entrant and the inventors were not hired from the parent. The interaction Initial hires from others * (1-spinoff) is the equivalent for inventors hired from firms other than the cited firm. Its coefficient is positive and significant (at the 10% level). Overall, an inventor hired by recent entrants increment the expected number of citations to firms other than their previous employer by 13%. These results largely conform to hypotheses 3a and 3b, which postulate that inventors hired by recent entrants contribute mostly by bringing industry specific knowledge rather than specific knowledge from their previous employer.

After introducing the initial hiring count variables, the coefficients of the # inventors hired from cited, and of the # inventors hired from others variables slightly dropped, but both are still significant. According to hypothesis 1b, the coefficient of # inventors hired from others should not be significant, as we did not expect the acquisition of industry specific knowledge to

15 Note the variables count inventors hired during the first five years of the firm, for a period of 5 years. This means inventors hired from the parent at year 5 will be counted in this variable up to year 9. Also at year 9 of the spinoff, this variable will only consider the inventors hired from the parent during year 5.

16 This considers the coefficients Hired from cited and Hired from cited * spinoff.

17 Note this includes inventors hired by spinoffs from firms other than the parent and all inventors hired by non-spinoff entrants during their first five years.

18 This corresponds to the coefficients Hired from other and Hired from other * (1-spinoff).
be important among incumbents. Model 3 incorporates a variation to understand how incumbents use the knowledge of moving inventors coming from different source firms. Our definition of incumbent, i.e. a firm older than 5 years old, admits a lot of variation within incumbents. Among our incumbents there will be firms with significantly more resources and capabilities than others. Thus, they will differ in terms of their needs for external knowledge, as well as in the value of its knowledge for external firms. A leading firm is likely to have more internal resources, and their inventors should be more valuable to other firms. During the period covered by our sample, 3 firms stand out in terms of number of patents: Texas Instruments, Motorola, and RCA.

We introduce two additional variables to measure the industry specific and firm specific learning that results from hiring inventors from these firms. “Leader” is a variable equal to 1 if the cited firm is Texas Instruments, Motorola, or RCA, and 0 otherwise. Hiring from cited * leader corresponds to the additional acquisition of firm specific knowledge that results from hiring inventors from any of these firms. The coefficient is negative and insignificant, which implies that inventors hired from these firms do not bring in more firm specific knowledge than inventors hired from other firms. We also define a variable that counts the number of inventors hired from these 3 firms, which we call “# inventors hired from leaders”19. This variable is used to measure the acquisition of industry specific knowledge that results from hiring inventors from the leaders. The coefficient estimate is positive and significant. Moreover, after introducing this variable, the coefficient of Hiring from others drops out of significance and is now close to 0. These results give a better understanding of the support for hypothesis 1b.

When hiring experienced inventors, incumbents benefit from accessing the knowledge generated at the inventor’s previous employer. The resulting acquisition of industry specific knowledge does not seem to be important, unless the inventor is hired from a leading firm. Moreover, although the coefficient associated with the acquisition of firm specific knowledge from leading firms was not significant, it is negative. This suggests that when incumbents hire inventors from leading firm they are less interested in acquiring firm specific knowledge. Instead, they are mostly looking for general knowledge about the industry.

Throughout the different models, the Local SV and Local not SV coefficients remained mostly unaffected. This is interesting, as it hints how different theories on the causes of the geographical localization of knowledge work in this setting. Breschi and Lissoni (2006) propose that the reason behind the geographical localization of knowledge found by Jaffe et al. (1993) is that moving inventors act as conduits of knowledge spillovers. As workers tend to stay in the same region when changing employers, knowledge diffuses through inventor mobility to

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19 This variable does not include the number of inventors hired from the cited firm in cases where the cited firm is one of the leaders. Otherwise, the variable would mix up acquisition of firm-specific and industry-specific knowledge. While for simplicity in the tables and in text we call this variable # inventors hired from leaders, a more accurate name would be: # inventors hired from leaders - # inventors hired from cited * leader
neighboring firms. The evidence we find conforms to this theory, but the residual effect captured by the \textit{Local SV} and \textit{Local not SV} suggests there are also other knowledge diffusion mechanisms in place\textsuperscript{20}. These could include the informal exchange of information between inventors of competing firms (von Hippel 1987) or the diffusion of knowledge through collaborative networks (Singh 2005).

If other knowledge diffusion mechanisms operate at the local level, spinoffs can access knowledge from their parents by ways other than inventor mobility. To test this, in model 4 we include the “\textit{Recent spinoff (10 yrs)}” dummy\textsuperscript{21}. This is equal to one if the citing firm is a spinoff of the cited firm that is 10 years old or younger. The coefficient of this variable is positive, large, and significant (at the 10\% level). Introducing the spinoff dummy causes the coefficient of \textit{Initial hiring from cited * spinoff} to drop out of significance. This suggests that the technical link that exists between parents and spinoffs goes above and beyond the transfer of knowledge that occurs from many inventors moving from parent to spinoff.

\section*{4.3 Robustness Checks and Placebo Test}

We implement several tests to determine if things other than learning could drive the coefficients estimated in the previous section. The first concern relates to whether the increase in citations we observe is the result of learning from moving inventors or is due to other events that caused both an increase in learning and in the hiring of experienced inventors. A first test, reported as models 5 and 6 in Table 4, consists of adding a variable counting the number of inexperienced inventors hired in the last 5 years from the observation date. This variable corresponds to the number of inventors that applied for patents at the citing firms for the first time during the past 5 years and that did not have any prior patent at any firm. If the increase in citations is not related to learning from experienced inventors, and instead is the result of something else that caused both learning and growth, the coefficient corresponding to hiring inexperienced inventors should also be positive and significant.

\textsuperscript{20} Estimating the models without any of the hiring variables yields bigger coefficients for \textit{Local SV} and \textit{Local not SV}, being 0.516 and 0.297 respectively. Thus, inventor mobility explains some, but not all, of the local diffusion of knowledge. After including the hiring variables, the \textit{Local SV} drops more than the \textit{local not SV} coefficient, implying that knowledge diffusion through inventor mobility is more important in Silicon Valley than in other areas.

\textsuperscript{21} Although throughout the paper we have defined recent entrant and recent spinoff as firms 5 years old or younger, the initial hiring variables are defined in a way that influences citing for 10 years. To be consistent, we let the parent influence the spinoff for a period of 10 years.
Table 4: Coefficient estimates of robustness checks and placebo test

<table>
<thead>
<tr>
<th></th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
<th>Model 9</th>
</tr>
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<tbody>
<tr>
<td># Inventors hired from cited</td>
<td>0.365***</td>
<td>0.136</td>
<td>0.275***</td>
<td>0.075***</td>
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<td></td>
<td>(0.081)</td>
<td>(0.110)</td>
<td>(0.083)</td>
<td>(0.025)</td>
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<tr>
<td># Inventors hired from others</td>
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<td>0.005</td>
<td>0.042**</td>
<td>0.036***</td>
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<td></td>
<td>(0.022)</td>
<td>(0.034)</td>
<td>(0.017)</td>
<td>(0.009)</td>
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<tr>
<td>Initial hiring from cited * spinoff</td>
<td>0.147</td>
<td>-0.058</td>
<td>0.178</td>
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<td>(0.212)</td>
<td>(0.343)</td>
<td>(0.183)</td>
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<td>Initial hiring from others * spinoff</td>
<td>-0.066</td>
<td>0.031</td>
<td>-0.053</td>
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<td></td>
<td>(0.108)</td>
<td>(0.091)</td>
<td>(0.094)</td>
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<td></td>
</tr>
<tr>
<td>Initial hiring from cited * (1-spinoff)</td>
<td>-0.080</td>
<td>0.032</td>
<td>-0.117</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.120)</td>
<td>(0.134)</td>
<td>(0.111)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial hiring from others * (1-spinoff)</td>
<td>0.093**</td>
<td>0.028</td>
<td>0.081*</td>
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</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.052)</td>
<td>(0.047)</td>
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<td></td>
</tr>
<tr>
<td>Log (Stock IC patents cited firm)</td>
<td>0.983***</td>
<td>0.962***</td>
<td>0.988***</td>
<td>0.672***</td>
<td>0.582***</td>
</tr>
<tr>
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<td>(0.021)</td>
<td>(0.021)</td>
<td>(0.021)</td>
<td>(0.046)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Log (Stock IC patents citing firm)</td>
<td>0.720***</td>
<td>0.738***</td>
<td>0.742****</td>
<td>0.731***</td>
<td>0.497***</td>
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<td>(0.050)</td>
<td>(0.059)</td>
<td>(0.055)</td>
<td>(0.052)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>Nr. Patents citing firm</td>
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<td>0.004</td>
<td>0.007**</td>
<td>0.005**</td>
<td>0.006***</td>
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<td>(0.006)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.001)</td>
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<tr>
<td>Local not SV</td>
<td>0.259*</td>
<td>0.163</td>
<td>0.276**</td>
<td>0.235***</td>
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<td></td>
<td>(0.146)</td>
<td>(0.142)</td>
<td>(0.128)</td>
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<tr>
<td>Local SV</td>
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<td>0.626****</td>
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<tr>
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<td>(0.141)</td>
<td>(0.125)</td>
<td>(0.133)</td>
<td>(0.168)</td>
<td></td>
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<tr>
<td># Inventors hired from cited * leader</td>
<td>-0.179</td>
<td>0.038</td>
<td>-0.117</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>(0.124)</td>
<td>(0.164)</td>
<td>(0.090)</td>
<td></td>
<td></td>
</tr>
<tr>
<td># Inv. hired from leaders</td>
<td>0.074</td>
<td>0.159***</td>
<td>0.032</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.046)</td>
<td>(0.055)</td>
<td>(0.038)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hiring of inexperienced inventors</td>
<td>0.002</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Recent spinoff (10 years)</td>
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<td>0.621*</td>
<td></td>
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<tr>
<td></td>
<td>(0.370)</td>
<td>(0.344)</td>
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<tr>
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<td>(0.207)</td>
<td>(0.213)</td>
<td>(0.207)</td>
<td>(0.274)</td>
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<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
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<tr>
<td>Dyads fixed effects</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parenthesis

In Model 5 we introduced only the “Hiring of inexperienced inventors” variable along with the controls. Its coefficient estimate is positive, small, and insignificant. The hiring of inexperienced inventors is highly correlated with the number of patents filed by the firm. Thus, Model 5 implies that even though hiring inexperienced inventors is associated with an increase in patenting (this is hardly surprising, as the numbers of hires are inferred from patent filings), it
is not related to an increase in the likelihood of citing patents of other firms. If in Model 5 we had not included the control variables, the coefficient of hiring inexperienced inventors would be positive, but this effect was removed by considering the effect of the growth of the firm\textsuperscript{22}. Model 6 is equivalent to Model 4 including the “hiring of inexperienced inventors” variable. The coefficients estimated in model 4 are unchanged after adding this new variable.

Another concern is whether the increase in citations is a result of hiring inventors, or if the inventors were hired after there was an increase in knowledge flows. To test this, we specify a placebo test that consists on trying to find an effect before the moving inventors are actually hired. If the increase in citations we attribute to hiring moving inventors is the result of changes within the organization that also lead to the hiring of experienced inventors, counts of future hiring should also have a positive effect. To implement this test, we re-compute all hiring count variables to considering inventors hired from time t+1 to t+5 (instead of inventors hired from t-4 to t). Observations for 1987 are dropped, as future hiring cannot be computed in this case. The coefficient estimates are presented under model 7 in table 4. The coefficients of Hiring from cited and Initial hiring from cited * (1-spinoff) are not significant in this model. This is reassuring, as it indicates that the effect of hiring does not occur until the inventors are really hired. Surprisingly the coefficient of Hiring from leaders is significant when measuring future hiring. While this question whether hiring mobile inventors leads to the acquisition of industry specific knowledge, it also suggests that the firms that are more likely to integrate varied knowledge are the ones that hire inventors away from leading firms. If we think that integrating varied knowledge is associated with perceived quality of the firm, this could also suggest that only organizations that are seen as high performers are able to lure inventors away from the leading firms. In a further attempt to capture differences for which the previous estimations may be unable to control, we experiment with using a conditional fixed effects negative binomial regression with dyads fixed effects. While this method has the ability to control for unobserved relationships between firms in a dyad, it has important limitations in this setting. Variables with no within dyad variation, such as Local SV and Local nSV, cannot be included. Dyads with no citations at any time cannot be included either, which eliminates 5714 out of 6337 dyads. Of the 623 dyads that remain, 29% have 10 or fewer observations. As the sample is drastically reduced, we do not attempt to estimate all of the interactions we specified in previous models and focus on obtaining the \# inventors hired from cited and \# inventors hired

\textsuperscript{22} We also experimented with including only the “Hiring of inexperienced inventors” variable. Its coefficient in this model was positive, but it becomes insignificant once we considered the control variables (Model 5), or alternatively citing firm fixed effects and the number of patents of the citing firms. This leads us to believe that any learning effect that could result from inexperienced inventors is removed after considering the growth of the firm.
from others coefficients while maintaining the control variables. The coefficient estimates of both hiring count variables, reported as Model 8 in Table 4, are positive and significant. Its magnitudes are smaller than in previous models, but they still imply there is an important increase in citations associated with moving inventors. It is reassuring that we are able to find statistical support for the main effects relying entirely on temporal variations. This is especially true considering that the dates of the movements inferred from patent data are inherently imprecise. It is also encouraging that after excluding most observations with zero citations the main effects are still present. In this conservative scenario, the coefficient estimates imply that each moving inventor is associated with an 8% increase in citations to patents of his previous employer, and with a 4% increase in citations to patents of each of the other firms.

5. Discussion

This paper proposes that firms that hire experienced inventors benefit in two ways. They gain access to knowledge developed at the inventors’ previous employers, and they also increase their ability to capture knowledge generated at other organizations. The latter is achieved by gaining access to the industry specific knowledge inventors accumulate throughout their careers. Incumbents and new firms will differ in their interest for firm specific and industry specific knowledge. The acquisition of industry specific knowledge is of little value to incumbents, because they already possess a wealth of it. On the contrary, this knowledge is the main reason young firms hire experienced inventors. The acquisition of firm specific knowledge from the inventor’s previous employer is beneficial for incumbents looking to acquire specific technologies. Its use is more limited at recent entrants, with the bulk occurring in spinoffs wanting to acquire technologies from their parents.

The statistical analysis supports the hypothesis that hiring mobile inventors facilitates the acquisition of firm specific and industry specific knowledge. Consistent with the theory outlined in this paper, spinoffs only benefit from the mobile inventor’s previous employer’s firm-specific knowledge if he is hired from the parent. Inventors hired by new firms from unrelated entities contribute mostly by bringing in industry specific knowledge. In terms of economic significance, the contribution made by an individual inventor hired from the parent in terms of firm specific knowledge is larger than the individual contribution made by an inventor hired from other firm in terms of industry specific knowledge. However, the overall effect in terms of industry specific learning is realized from a larger pool of inventors. Even with many inventors moving from the parent to the spinoff, there is a comparable or larger group of

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23 If we include all of the explanatory variables of previous models in the model with dyad fixed-effects, the coefficients do not change much, but the standard errors increase due to the reduction in sample size. The only significant differences that arise are with the coefficients Hiring from cited * spinoff, and Recent spinoff. Both these coefficients become much smaller and insignificant. This is easily explained considering that most of the relationship between parents and spinoffs is now captured by the dyad fixed effect.
inventors who are hired from other firms. This makes the overall acquisition of industry specific
to be smaller than the contribution of inventors hired by incumbents from lesser firms. The key
knowledge economically significant for recent entrants.

In the case of incumbents, we find that they only acquire disciplinary knowledge when
hire inventors from leading firm. We find evidence, although limited, that the contribution of
hiring inventors from leading firms in terms of firm-specific knowledge appears
hiring inventors from leading firms seems to be the acquisition of
industry specific knowledge.

These results provide an interesting interpretation of the benefits recent entrants in
Silicon Valley enjoyed. The larger availability of workers in this cluster made it easier for recent
to put together their founding team. The contribution of most of these inventors is
industry specific knowledge and thus should be highly substitutable. Moreover, the inventors
who apparently contributed the most in terms of industry specific knowledge came from large
patenters, all of which were located out of Silicon Valley during the time of this study. While the
availability of workers may ease the entry of startups, it does not seem to provide a sustainable
competitive advantage. Any able firm that located in Silicon Valley could have assembled a
team of knowledgeable workers, and presumably, a firm that located close to leading firms like
RCA, Motorola, or Texas Instruments, may have been in a better position to do so.

What seems to have been determinant on the success of entrants in Silicon Valley is
their heritage. Most of the firms that entered in Silicon Valley were spinoffs, and they did rely
heavily on their parents to hire inventors from. There were significantly fewer spinoffs in other
regions, but in these few cases heritage also played an important role. Why were there so few
spinoffs outside of Silicon Valley is an interesting question. While answering this question is a
daunting task that is beyond the scope of this paper, we can still offer some conjectures based
on our analysis. It probably had more to do with characteristics of firms outside of Silicon Valley
than with characteristics of the regions they were located in. If high quality ideas for spinoffs
had been generated outside of Silicon Valley, potential entrants should have been able to
overcome the difficulties associated with being located outside the cluster. Only marginal
projects should be prevented to enter due to the relatively higher cost of entry outside of
Silicon Valley.

As with other studies based on patent data, our results are not exempt from limitations.
While it is reasonable that young firms hire experienced inventors to acquire general
knowledge and develop their internal capabilities, the patterns we observe could also result
from deliberate attempts to hide the acquisition of proprietary knowledge from mobile
inventors. To prevent knowledge leakage firms often use varied mechanisms, including
covenants not to compete (Marx, Strumsky, and Fleming 2009) and aggressive intellectual
property litigation (Agarwal, Ganco, and Ziedonis 2009). In order to circumvent these
restrictions and avoid costly litigation, firms could try to hide the mobile inventors’ work by relying on secrecy rather than patents to protect innovations.

Since Jaffe et al. (1993) published their work on the geographical localization of knowledge, there have been several works that aim to explain why knowledge diffuses locally. Inventor mobility seems particularly suited for this purpose. The local nature of knowledge diffusion can been explained by inventors taking knowledge with them as they change employers and moving mostly to nearby firms (Breschi and Lissoni 2006). While we find support for this theory, our results also indicate that inventor mobility cannot explain all knowledge flows. There exists a residual local knowledge diffusion effect that is stronger in Silicon Valley. Moreover, the technical link between parents and spinoffs goes beyond the knowledge taken by inventors who join the spinoff. This sheds additional light on the locational choice of spinoffs. Evidence from the tire industry suggests that spinoffs of firms located outside an agglomerated region choose to stay local, despite the potential benefits of agglomeration economies in other areas (Buenstorf and Klepper 2010). The spinoffs that are more likely to locate close to the parent are those that plan to compete at the forefront of their field (Berchicci, King, and Tucci 2011). If the only way spinoffs tap into their parents’ knowledge is by hiring experienced inventors away from them, their location should not be geographically bounded. If this were the case, spinoff would locate in the region that offers the greatest agglomeration economies and generously compensate the workers they need from the parent in order to get them to relocate. Either the additional channels of knowledge spillovers from parents to spinoffs require geographical proximity, or, as suggested by Figueiredo et al. (2002), the gains from local pre-entry knowledge outweigh the potential benefits of agglomeration and urbanization economies in distant regions.
Bibliography


Appendix: Description and summary statistics of variables used in econometric models.

Unit of analysis are dyads of firms. One firm in the dyad is called the cited firm, while the other is the citing firm. There is one observation per dyad from 1967 to 1987, unless one of the firms in the pair didn’t exist in that year.

Dependent variable:

| Citations (t) | Unit of analysis are dyads of firms. One firm in the dyad is called the cited firm, while the other is the citing firm. There is one observation per dyad from 1967 to 1987, unless one of the firms in the pair didn’t exist in that year. Dependent variable is the number of citations in patents from the citing firm applied in year t to patents of the cited firm. |

Explanatory variables:

| Hired from cited (t) | Number of inventors hired by the citing firm from the cited firm between t-4 and t. |
| Hired from others (t) | Number of inventors hired by the citing firm from any firm but the cited firm, from t-4 and t. |
| Spinoff | Equal to 1 if the citing firm is a spinoff of the cited firm, and it entered between t-4 and t. |
| Spinoff (10 yrs) | Equal to 1 if the citing firm is a spinoff of the cited firm, and it entered between t-9 and t. |
| Initial hiring from cited (t) | Number of inventors hired by the citing firm from the cited firm, while the citing firm was younger than 5 years old. The variable correspond to the sum of the hiring that occurs between t-4 and t. |
| Initial hiring from cited (t) | Number of inventor hired by the citing firm from any firm but the cited firm, while the citing firm was younger than 5 years old. The variable correspond to the sum of the hiring that occurs between t-4 and t. |
| Leader | Equal to 1 if the cited firm is Texas Instruments, Motorola, or RCA. |
| Hiring from leader (t) | Number of inventors hired by the citing firm from TI, Motorola, or RCA between t-4 and t. |

Control variables

| Log (Stock IC patents cited firm (t)) | Log of the number of IC patents applied by the cited from the start of the sample to t. |
| Log (Stock IC patents citing firm (t)) | Log of the number of IC patents applied by the citing from the start of the sample to t. |
| Citing patents (t) | Number of patents filed by the citing firm during year t. |
| Local SV, local not SV | Equal to one if the citing and the cited firm are located in the same region, and that region is or isn’t SV. |