Inventor Mobility, Knowledge Spillovers and Spinoff Entry in the U.S. Semiconductor Industry: Regional Patterns, Determinants, and Learning Implications.

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Cristobal A Cheyre Forestier

B.S., Industrial Engineering, Pontificia Universidad Catolica de Chile
M.S., Engineering Management, Pontificia Universidad Catolica de Chile

Carnegie Mellon University
Pittsburgh, PA

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Abstract

This dissertation systematically analyzes the link between inventor mobility and knowledge diffusion in the semiconductor industry. It looks at how incumbents and recent entrants benefit from hiring inventors by analyzing geographical mobility patterns, the determinants of inventor mobility, and the types of learning that results from hiring. The analysis is based on data on the origins of all semiconductor producers with larger sales, and on patent filings and patent citations. Three papers comprise the dissertation.

The first paper argues that the higher mobility of inventors in Silicon Valley can be explained mostly through the rate of spinoff entry in the region. The empirical evidence shows that inventor mobility was high in Silicon Valley since spinoffs started entering in large numbers, which happened before the industry clustered there. Agglomeration economies and the ban of non-compete covenants can facilitate the continued entry of spinoffs, but they cannot explain the initial wave of entry. Further evidence of the effect of entry on mobility rates is provided by spinoffs outside of Silicon Valley, which also hire many inventors from their parents and other local firms.

The second paper identifies and tests several drivers of worker turnover associated with matching and learning. Incumbents, recent entrants, and spinoffs have different goals when hiring experienced inventors. Incumbents hire many workers without prior patents, while younger firms hire mostly experienced inventors. For inventors hired by incumbents, the main determinant is matching. Instead, movements from parent to spinoffs seem to be motivated by the acquisition of knowledge from the parent. None of the drivers previously identified seem to apply to recent entrants.

The last paper analyzes the effect of hiring experienced inventors on the citations made by the hiring firm. In movements to incumbents, or from parent to spinoffs, there is an increase in citations from the hiring to the origin firm. However, movements to recent entrants are associated with increases in citations to other firms. This is related to what firms learn from hiring. While incumbents and spinoff access firm specific knowledge from moving inventors, recent entrants seem to be more concerned with the knowledge about the industry that the inventor possesses.

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1 Introduction

The geographical concentration of economic activity has captured the interest of scholars since the birth of modern economics. As early as 1776 Adam Smith (1863) noted that the division of labor that arises when markets operate within geographical limits underlies the very nature of the prosperity of cities. The work of Alfred Marshall (1890) on "external economies of scale" is to this day the starting point for explaining the benefits of clustering. Throughout the years geographical economists have documented the features of agglomeration of economic activity [See Rosenthal and Strange (2004) for a survey of the empirical literature] and developed theoretical models to explain how they operate [See Duranton and Puga (2004) for a survey on the theoretical literature]. Traditionally the benefits of clustering are associated with economies achieved thanks to lower transportation costs, labor pooling, and knowledge spillovers (Marshall, 1890). More recently, clusters have been explained through either the existence of increasing returns to scale that operate at the regional level (Krugman 1991) or due to the importance of knowledge spillovers in knowledge-intensive industries (Audretsch & Feldman 1996).

While the existence and benefits of clusters in different industries are well represented in the literature, little is known about why some regions get to be clustered in the first place and others do not. Obvious causes, like the presence of natural advantages, cannot explain why regions without any apparent advantage host industry clusters. In these cases a related phenomenon that can lead to the emergence of clusters is the concentration of firm entry. Several works propose that firm entry concentrates in regions where related activity is already in place (Figueiredo, Guimarães & Woodward 2002; Rosenthal & Strange 2004; Buenstorf & Klepper 2010). Others suggest that entrepreneurs play a key role in the formation of clusters, as they attract additional entry while

developing the resources necessary for their firms. (Feldman 2001, Feldman and Francis 2001, and Feldman et al. 2004). Most of these entrepreneurs were employed at local firms before starting their own ventures. In both these accounts, knowledge spillovers figure prominently among the reasons entrepreneurs choose to remain local. Conceivably, entrants choose to remain local to benefit from contextual knowledge that outweighs the economies that may exist in distant clustered regions (Buenstorf & Klepper 2010; Figueiredo et al. 2002).

In high-tech industries, employees leaving to form spinoffs have been particularly prevalent and may have an important role in the creation of clusters (Klepper 2010). Spinoffs are tightly related to inventor mobility and knowledge spillovers. The very creation of a spinoffs is marked by the movement of a worker from the parent, often to develop an idea he had while working there (Klepper & Thompson 2010). Even though spinoffs retain no formal ties to the firm their founders came from, they inherit market and technical know how (Agarwal et al. 2004; Franco & Filson 2006), as well as general and regulatory knowledge (Chatterji 2009), from them. The process that leads to spinoff entry is self-reinforcing and fosters the growth of industry clusters. Spinoffs of leading firms are superior performers, and their performance affects the rate at which they generate further spinoffs (Klepper 2010).

The aim of this dissertation is to analyze systematically the role of inventor mobility in firm entry, particularly of spinoffs, in the semiconductor industry. The study is set up from the time the industry began to cluster in the region south and west of San Francisco, until "Silicon Valley" was already the dominant region. This period is of particular interest, as it can shed light on what factors contributed to the creation of the cluster. The main focus of the dissertation is to determine to what extent spinoffs rely on

experienced inventors, how the entry of spinoffs affects regional inventor mobility rates, and how spinoffs use the previous knowledge of the inventors they hire. Information from patent filings is used to infer inventor mobility, and patent citations are employed to observe knowledge flows. Detailed information on new firms is also necessary, including their date of entry, location, and heritage. The body of the dissertation is composed by three independent papers, presented in chapters 2-4. Chapter 5 offers a summary of the main findings and some concluding remarks.

The first paper, Chapter 2, discusses how entry of spinoffs affects inventor mobility rates at the regional level. The central idea of this chapter is that if new firms disproportionately rely on hiring experienced inventors from local firms to staff their initial operations, the concentration of spinoff entry will affect the rate of inventor mobility within a region. This is certainly plausible. Due to the technical link that exists between a spinoff and its parent, the experience of the parent's employees should be valuable to the spinoff. New firms should also prefer hiring local inventors, as this entails lower search costs and avoids paying reallocation premiums. Overall, this process means that the higher rate of spinoff generation in Silicon Valley will result in an increase in worker mobility there. Results indicate that without considering movements to recent entrants, the rate of inventor mobility in Silicon Valley is only marginally higher than the rate in other regions.

After establishing the importance of firm entry over inventor mobility in the first paper, the second paper, Chapter 3, examines the determinants of inventor mobility. This chapter first identifies several drivers of mobility based on prior literature and then analyzes how they relate to the needs of incumbents, recent entrants, and spinoffs. The drivers suggested by prior works can be summarized in two basic categories: matching and

learning. Changes of employment due to matching occur when the inventor moves to a firm that offers a better fit for his skills. Changes related to learning happen when firms hire experienced inventors in order to access their knowledge. Findings suggest that in the case of recent spinoffs, drivers related to learning are the main determinants of mobility. When the hiring firm is an incumbent, it seems that matching is the primary motivation. None of the commonly suggested drivers exhibits any significance for inventors hired by recent entrants from firms other than their parent. These patterns motivate the next chapter, which analyzes how recent entrants use the previous knowledge of the inventors hired during their first few years.

The last paper, presented in Chapter 5, explores how new firms leverage the experience of their initial team of inventors. The learning-by-hiring literature suggests that firms in need of acquiring knowledge from competitors can resort to hiring workers away from them. As explained in Chapter 4, this does not seem to be the main concern of recent entrants when hiring experienced inventors. The theory advanced in this chapter is that because new firms have no prior history and limited resources, they hire experienced inventors in order to acquire general knowledge about the industry and to improve their knowledge brokering capability. The needs of spinoffs for specific knowledge are restricted to knowledge from the parent, which is necessary to realize the idea that led to the spinoff. Results support this theory, although the relocation of inventors cannot solely explain the transfer of knowledge from parent to spinoff.

2 Spinoffs and the Mobility of US Merchant Semiconductor Inventors[1]

Abstract

Data on assignees of patenters is used to analyze the mobility of semiconductor inventors. Exploiting data on the origins of semiconductor producers with larger sales, we argue that the higher mobility of semiconductor inventors in Silicon Valley is in great part due to the entry of spinoffs there. Our empirical evidence suggests that spinoff entry promoted mobility in Silicon Valley even before the industry was clustered there. Agglomeration economies and the ban on non-compete covenants may influence spinoff entry, but spinoffs promote mobility even in the absence of those conditions. As most of the greater inventor mobility in Silicon Valley corresponds to inventors moving from incumbents to recent entrants, the benefits that arise from greater mobility rates will be disproportionately reaped by new firms.

2.1 Introduction

An important element in the performance of an economy is its ability to reallocate factors of production in response to changes in supply and demand conditions. In innovative industries, one of the most important factors is inventive labor. A number of recent studies use patent data to analyze the mobility of inventors, who are inferred to have changed jobs when the assignee of their patents changes (Trajtenberg, Shiff & Melamed 2006). Issues analyzed include the types of inventors firms hire (Song, Almeida

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& Wu 2003; Trajtenberg & Shalem 2009; Palomeras & Melero 2010), whether the movement of inventors provides a conduit for technological spillovers and the diffusion of knowledge (Almeida, Dokko & Rosenkopf 2003; Rosenkopf & Almeida 2003; Song et al. 2003; Agarwal, Ganco & Ziedonis 2009; Corredoira & Rosenkopf 2010), the effects of employee non-compete covenants (Marx, Strumsky & Fleming 2009) or of firm acquisitions (Hussinger 2007), and the effects of mobility on inventor productivity (Hoisl 2007; Hoisl 2009; Nakajima, Tamura & Hanaki 2010).

Inventor mobility also figures prominently in the literature on industry agglomeration. If firms in an industry cluster geographically, it can make it less costly for workers to change jobs, leading to greater local worker mobility. The mobility of workers in turn appears to be a key factor explaining the findings of Jaffe, Trajtenberg & Henderson (1993) that citations to patents tend to be localized (Breschi & Lissoni 2007). This suggests that the diffusion of knowledge across firms will occur faster in industry clusters (Almeida & Kogut 1999; Breschi & Lissoni 2007), making it easier for firms in clusters to keep up with the technological frontier in their industry. All firms in clusters will benefit, giving rise to agglomeration economies. Such economies impart a self-reinforcing character to industry agglomerations (Duranton & Puga 2004).

An additional reason clusters may be distinguished by high rates of knowledge diffusion is related to entry by spinoffs of incumbent producers. Recent studies in a variety of industries, including automobiles (Klepper 2007; Klepper 2010), tires (Buenstorf & Klepper 2009), semiconductors (Klepper 2007; Klepper 2010), disk drives (Christensen 1993; McKendrick, Doner & Haggard 2000; Franco & Filson 2006), and biotechnology (Mitton 1990; Romanelli & Feldman 2006), show that clusters in these industries were distinguished by high rates of indigenous spinoff entry. Entrants need to hire workers to

staff their operations. A natural place for spinoffs to hire from is their parent firm. To the extent spinoffs hire disproportionally from their parents and other local firms, rates of labor mobility and associated diffusion of knowledge will be higher in clusters.

This paper analyzes the influence of spinoff entry on regional labor mobility rates. The setting of our study is the semiconductor industry, which is notoriously clustered in Silicon Valley, a region that is also famous for its high level of job hopping (Saxenian 1994, pp 34-5). A novel feature of our analysis is that we exploit data on the origins of all semiconductor producers whose sales exceeded a minimum threshold to analyze the nature of the flows of inventors between firms. Our sample starts in the late 1960s, when the industry was starting to cluster in Silicon Valley. Many of the firms studied were spinoffs of other incumbent semiconductor producers that located in Silicon Valley, but the sample also considers entrants across all regions of the US. Compared to inventors located elsewhere, the mobility rate of inventors in Silicon Valley is about 3 times higher. However, most of the increased mobility in the region corresponds to inventors moving from incumbents to recent spinoff entrants. Spinoffs hire many inventors from their parents in their first few years, both in and out of Silicon Valley, but the huge number of spinoffs that are constantly created in Silicon Valley is distinctive and elevates the region's overall mobility rate.

This paper contributes to the existing literature by identifying the hiring decisions of recent spinoffs as an important determinant of inventor mobility at the firm and regional level. That so much of the job hopping observed in Silicon Valley can be explained by the entry of spinoffs is an intriguing result. This begs for some consideration on how the spinoff process contributed to the clustering of the industry, and how the availability of workers facilitates the entry of spinoffs. Factors that may have eased the

entry of spinoffs in Silicon Valley include agglomeration economies, either through labor pooling or knowledge spillovers, and the inability to enforce non-compete covenants. We ponder how these factors might have influenced the hiring decisions of recent entrants and find some results that highlight the importance of spinoffs. Overall, we find a strong influence of spawning over a firm's inventor mobility and over the mobility of inventors of nearby firms, a result that is not restricted to Silicon Valley. In fact, spinoffs outside of Silicon Valley hire even more inventors from their parents than do spinoffs in Silicon Valley. This leads us to believe that the main effect of clustering and non-compete agreements is facilitating firm entry. The staffing process adopted by new firms in and outside of Silicon Valley has comparable effects over mobility rates at their parents and other nearby firms, but there are far less spinoffs outside of Silicon Valley.

The paper is organized as follows. In Section 2 we develop a theoretical framework to explain how spinoffs hire their initial staff. In Section 3 we describe how the data on firms, their heritage, and their patents were compiled, and present some broad patterns of this data in Section 4. In Section 5 we analyze statistically the determinants of inventor mobility and regional variations in mobility rates, and section 6 present some additional robustness analysis. Section 7 provides an analysis of how our results relate to the micro-foundations of agglomeration economies. Finally, in Section 8 we discuss our findings and offer concluding remarks.

2.2 Hiring Choices by Spinoff Entrants and its Effect on Inventor Mobility

The semiconductor industry began after the invention of the transistor at Bell Labs in 1947. The first firm of this industry to settle in Silicon Valley was Shockley Semiconductor Laboratory, which was founded by William Shockley with the intent of developing the first silicon transistor. The industry did not begin to cluster in Silicon Valley until after the entry of Fairchild Semiconductor in 1957, which was founded by eight of Shockley's employees who decided to leave after he abandoned his initial intentions. Fairchild pioneered the integrated circuit in the early 1960s, but it was racked by a number of problems, leading many of its top employees to leave and found their own firms. Its most prominent spinoffs were National, Intel, and AMD, which were founded in 1967, 1968, and 1969 respectively (Klepper 2009).

When our dataset begins, the late 1960s, there was an incipient cluster in Silicon Valley, which was comparable in size to the historical regions of the industry: Boston, New York, and even Los Angeles. By 1966, 11 spinoffs had entered in Silicon Valley, including Fairchild and 5 of its spinoffs. But from 1967 to 1975, 49 additional spinoffs entered in Silicon Valley. This significant entry elevated the market share of the region's firms to 38% of the US semiconductor industry. Towards the end of our dataset, the late 1980s, over 100 firms had entered in this region, capturing roughly half of the market (Klepper 2009).

Empirical evidence shows that semiconductor inventors located in Silicon Valley changed employers more frequently than their peers from other regions (Almeida & Kogut 1999; Saxenian 1994). Industry clustering and non-enforceable non-compete covenants

have previously been considered as explanations for these observations (Fallick, Fleischman & Rebitzer 2006; Gilson 1999). Yet, the huge number of spinoffs in the region is also likely to have influenced this heightened mobility, as these entrants needed to hire an initial staff of workers. To understand this process, it is important to reflect on the hiring decisions of new entrants, especially spinoffs.

Existing work (Angel 1989) suggests that small and specialized producers prefer to hire mostly local engineers with work experience when they enter. The presence of local incumbents from which they can hire is thus an important benefit. The first natural source for a spinoff to hire experienced inventors from is its parent. While spinoffs are nominally separate entities with no formal connection to the parent, they inherit technical knowledge (Klepper & Sleeper 2005) from them, and the quality of their technical and market pioneering capabilities is highly related to their roots (Agarwal et al. 2004). These knowledge spillovers need a channel to materialize, and a particularly suitable conduit is the mobility of inventors (Buenstorf & Klepper 2009; Franco & Filson 2006). Moreover, it has been widely suggested and documented that, in most cases, the very idea that led to the spinoff is based on work the founder did while employed at the parent (Pakes & Nitzan 1983; Klepper & Sleeper 2005; Cassiman & Ueda 2006; Klepper & Thompson 2010). In such cases, the founder's former co-workers whose knowledge is more relevant to the spinoff should be particularly willing to join the venture if properly compensated. In addition, when spinoffs are formed, they tend to stay in the same region as their parents to be able to leverage the founder's pre-entry knowledge about the region (Buenstorf & Klepper 2010). This proximity further helps the process of hiring inventors from the parent.

Spinoffs probably can not hire all the inventors they need from their parents and thus will also recruit employees from other sources. It is easier for the spinoff to recruit people from other local firms, as their social networks and knowledge about the region will make it easier to find prospective employees (Buenstorf & Klepper 2009). Hiring inventors from distant regions is more costly, not only because search costs are greater, but also because prospective employees have less information about the firm they are joining and are likely to demand higher risk premiums.

Overall, spinoff entry will lead to an increase in regional employee mobility rates, as spinoffs locate close to their parents and hire inventors away from them. Once they hire all the inventors they can from the parents they turn to other local incumbents. Thus, we hypothesize that:

Hypothesis 1a: The mobility of a firm's inventors will be directly related to the number of recent spinoffs it spawned.

Hypothesis 1b: The mobility of a firm's inventors will also depend on the number of spinoffs of other neighboring firms.

Not all the regions where the semiconductor industry was concentrated were equal. As noted above, without any doubt the most notable of these regions is Silicon Valley, which was emerging as a significant player in semiconductors when our sample starts. The industry became famously clustered there, where heightened levels of job hopping were also present (Saxenian 1994, pp. 34-5). Almeida and Kogut (1999) document a rate of labor mobility in Silicon Valley roughly three times that of other regions. Semiconductor firms located in Silicon Valley also had a roughly five times higher spinoff rate than firms elsewhere, and almost all of these spinoffs stayed in the region (Klepper 2010).

Several aspects can help explain this high spinoff rate. First and foremost, firms such as Fairchild and Signetics, which introduced major innovations and became leading players in the industry, had already been operating for some time in the region. Firms with high technical and market knowledge are more likely to generate spinoffs, which in turn are more likely to be high performers (Agarwal et al. 2004; Franco & Filson 2006; Buenstorf & Klepper 2009). As noted above, spinoffs stay close to their parents (Buenstorf & Klepper 2010), which thus fuels entry in this region. Besides having important firms, Silicon Valley had other characteristics that made it a fertile ground for spinoffs. Among them were the legal restrictions to the enforcement of non-compete agreements (Gilson 1999; Marx et al. 2009) and a recognized entrepreneurial culture (Saxenian 1994). The former also held for other semiconductor firms located in the state of California.

Out of Silicon Valley there were also several significant semiconductor producers. In fact, none of the initial leaders of the industry was located in Silicon Valley. Most of these key players were diversifying firms that had produced vacuum tubes or other electronics before the invention of the transistor (Klepper 2010). The most notable of these firms were RCA in New Jersey, Motorola in Arizona, and Texas Instruments in Texas. While these firms had a few spinoffs, including some that got to be leading firms, their spawning levels were negligible compared to those among Silicon Valley firms (Klepper 2009).

Over time, the initial leaders lost preeminence to the Silicon Valley entrants, especially after the emergence of the integrated circuit (Lécuyer 2006). This loss of technical leadership, along with difficulties to recruit inventors, could have affected the rate of spinoff generation outside of Silicon Vallley. Spinoffs outside of California would be likely to face difficulties in hiring inventors from their parents due to enforceable non-

compete agreements (Gilson 1999). Difficulties could also have come from the fact that hiring workers from large and well-established firms, which also pay higher wages, is difficult. Brown, Hamilton and Medoff (1990), as well as Davis, Haltiwanger and Schuh (1998) find that the mobility rate of U.S. workers within industries is lower in larger firms. Specifically for scientists and engineers, Elfenbein, Hamilton and Zenger (2010) report that job turnover declines sharply with firm size. Similarly, in a survey of semiconductor engineers, Angel (1989) finds that job tenure is negatively related to size of the firm and total worker experience.

The difference in the rate of generation of spinoffs between Silicon Valley and other regions has direct consequences for inventor mobility. Following the logic of hypothesis 1, worker mobility will be higher in regions where many spinoffs are being created. This logic can be further refined to consider the differences between Silicon Valley and other regions. Spinoffs outside of Silicon Valley had fewer neighboring firms with the necessary competences to hire inventors from. As a result, one could expect spinoffs out of Silicon Valley to rely more heavily on hiring inventors away from their parents. Moreover, they are also likely to exhaust all movable workers from the region, including the parent and the few other source firms, forcing them to turn to firms in other regions. Thus, we hypothesize that:

Hypothesis 2: Spinoffs in Silicon Valley hire a greater percentage of their initial workers from local firms but are expected to hire a smaller percentage of these workers from their parent when compared with spinoffs in other regions.

Hypothesis 3: The entry of spinoffs outside of Silicon Valley will affect the turnover rate of workers in all regions.

The hypotheses above suggest that the movement of workers between parents and spinoffs is quite important to understand the patterns of mobility in a region. Thus, it is relevant to reflect on the patterns of subsequent mobility of workers who had already moved from parent to spinoff. An important reason why spinoffs hire inventors from their parent is because they are experts on the technology the spinoff developed. This implies that the fit between these workers' ability and the spinoffs' requirements will be very good. According to the labor markets literature, the fit between workers and firms is a key determinant of job turnover (Jovanovic 1979; Topel & Ward 1992). Besides technical considerations, the social connections of founders also play a role in the identification of potential employees and in convincing them to join the spinoff (Stuart & Sorenson 2005). This will be especially relevant for workers of the parent firm, where the spinoff founder would have a variety of connections among co-workers. Since workers recruited from inventors' collaborator networks exhibit greater productivity and longer tenure (Nakajima et al. 2010), this too should reduce the probability of future mobility of inventors that moved from parent to spinoffs. These leads to the following hypothesis:

Hypothesis 4: Among workers who moved at least once, movers from parent to spinoff will be less likely to move again.

2.3 Data

Testing our hypotheses requires data on worker mobility rates and also on the heritage of semiconductor producers. Tracing the heritage of semiconductor producers is particularly challenging. It requires identifying which entrants were diversifiers versus new firms, and for new firms who the founders were and where they previously worked.

A unique resource compiled by the trade association Semiconductor Equipment and Materials International called the Silicon Valley Genealogy traced the heritage of all the semiconductor firms that entered in Silicon Valley through 1986. For each entrant, it lists its founders in order of importance, where founders are individuals who organized a firm and initially worked in it. We were also supplied with an annual itemization of the sales of the largest firms in the industry from 1974 to 2002 compiled by the consulting firm Integrated Circuit Engineering (ICE). Each year all firms whose sales exceeded a minimum threshold, which as of 1986 was less than 0.1% of the total sales of all U.S. firms, were listed. Between the Silicon Valley Genealogy and other sources, Klepper (2009) was able to trace the heritage of nearly all of the 101 ICE firms that entered by 1986, including their year of entry and exit. Four additional ICE firms entered in 1987, and we were also able to trace their backgrounds. A firm was classified as a spinoff if its main founder previously worked for another semiconductor firm, and the last semiconductor firm where the main founder worked was designated as the spinoff's parent.

To analyze worker mobility, all the patents from 1970 to 2002 in five main semiconductor classes were downloaded from the USPTO web site, and the firm identifiers[2] in the 2004 update of the NBER database (Hall, Jaffe & Trajtenberg 2001) were used to determine which of these patents were assigned to the ICE firms. 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). These patents accounted for between 60% and 70% of the patents issued to the Silicon

[2] These firm identifiers are based on the original assignee of the patent. Our results are thus not affected by subsequent reassignments that occur as a result of the "market for innovations."

Valley semiconductor producers on our list, which were mainly semiconductor specialists.[3] In contrast, for larger diversified firms like RCA, TI, and Motorola that were located outside of Silicon Valley, these five classes encompassed roughly a third of their patents. Our data on spinoffs pertain only to the semiconductor spinoffs of the ICE firms. Consequently, we need to restrict the analysis to semiconductor inventors, as we will not be able to explain the mobility of other inventors even if it was related to the formation of (non-semiconductor) spinoffs.

Eighty-one of the ICE firms in our dataset were assigned patents, reflecting the fact that even within our sample of major producers, the smaller firms were not assigned any patents. As such, our sample contains all the main patenters among the merchant producers in the period we consider, which begins in the mid 1960s when the earliest patents in our sample were applied for. The 81 firms are listed in the Appendix along with information about their heritage, patents, and job mobility.

We sorted all of the patents by inventor. For patents beginning in 1976, we used Lai, D'Armour & Fleming (2009) to deal with subtle differences in the way some inventors' names were recorded on their patents. For earlier patents the classification was done by hand. We also adjusted the classifications when merited based on an individual review of the patents issued to each inventor.[4] Each inventor's patents were ordered by

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[3] These classes have been singled out in a number of other studies of the semiconductor industry, including the Office of Technology Assessment & Forecast (1981, 1983), Ziedonis (2003), Oettl and Agrawal (2008), and Corredoira and Rosenkopf (2010).

[4] For example, Lai et al. (2009) distinguished Michael Allen, who was granted five semiconductor patents between 1981 and 1987 that were assigned to AMD, and Michael J. Allen, who was granted 15 patents between 1988 and 1995 that were assigned to Intel. The facts that the Intel patents followed quickly those at AMD, and both Intel and AMD are semiconductor producers, and the closeness of the names led us to classify these two inventors as the same person.

date of application. An observation involves two consecutive patent applications by the same inventor, denoted as A_1 and B_2, where the subscript denotes the application date of the patent (1 refers to the first patent, 2 to the second) and A and B denote the firm assignee of each patent. We restrict observations to cases where both firm A and firm B are on our list, the two patents are classified into one or more of our five semiconductor classes, and the inventor did not apply for another patent (in any class) assigned to a firm not on our list between dates 1 and 2.[5]

If firm A and firm B are different in observation (A_1, B_2), a job change may have occurred. If firm B acquired firm A in the year before date 2 or earlier, then the first patent is considered as belonging to firm B (so no job change occurred). We discovered a number of observations (A_1, B_2) where the inventor actually moved not from firm A to firm B but from firm B to firm A before date 1. These cases occurred when firm B applied for a patent in the inventor's name after he had left firm B and applied for a patent at firm A. We inferred these cases from the full history of an inventor's patents

[5] We checked for patents assigned to firms not on our list by collecting all the patents of each inventor in our sample from Lai et al. (2009) and used the NBER database to determine the firm to which each patent was assigned. This covers only patents granted since 1976. Consequently, for observations where date 1 is before 1976 we cannot rule out a patent applied for by the inventor between dates 1 and 2 that is assigned to a firm not on our list.

and adjusted moves accordingly.[6] A small number of other cases were more complicated and were adjusted on individual base.[7]

Dating moves was also challenging. It might be thought that for observations (A_1, B_2) involving a move, the move occurred between dates 1 and 2. However, the above case indicates that the move could have taken place before date 1. Indeed, we randomly sampled 20 inventors with consecutive patents assigned to different firms and found that when we could reconstruct the inventors' work history, on average the inventor moved .25 years *before* date 1.[8] This suggests that date 1 is a pretty good estimate of when the

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[6] For example, suppose that corresponding to an observation (A_1, B_2) we found the inventor's successive patents were B, B, A_1, B_2, A, A—i.e., two were assigned to firm B and applied for before date 1 and two were assigned to firm A and applied for after date 2. In these cases, patent B_2 was likely applied for by firm B in the inventor's name after he had moved to firm A (and already applied for a patent at firm A). In such cases, we included the first two B patents as one observation, the second B patent and the A_1 patent as a second observation, the A_1 patent and the second A patent as a third observation, and the third and fourth A patents as a fourth observation.

[7] For example, Walter C. Seelbach had 24 patents over the period 1966 to 1994, including two in 1967, two in 1970, and three in 1978. Except for one of the 1970 patents, which was assigned to Fairchild, all the rest were assigned to Motorola. The patent assigned to Fairchild involved a co-inventor whose name was listed first, which may have played a role in the assignment of the patent. In cases like this, we assumed the inventor had always worked at Motorola and the patent assigned to Fairchild was due to the co-inventor.

[8] Among the 13 moves that we could date, three occurred within three years before the last patent at the prior employer, seven in the same year as the last patent at the prior employer, and three within two years after the last patent at the prior employer. The number of years between the move and the first patent at the new employer varied from 1 to 11 years. Among all our observations, the average time between dates 1 and 2 was 1.7 years when the two patents were assigned to the same firm and 6.2 years when assigned to different firms. The difference could be due to a number of factors, including inventors needing time to acclimate themselves to their new environment when they change employers and/or adding new managerial responsibilities that could slow down their patenting. The latter factor is well illustrated by Andrew Grove, who moved from Fairchild to Intel in 1968 when Intel was founded. He worked in R&D at Fairchild, and his last semiconductor patent there was in 1968, the year he moved. At Intel he was primarily a manager, and his first semiconductor patent at Intel was in 1993. This was longest time between an inventor's consecutive patents at different firms of any inventor who moved in our sample.

inventor moved. Accordingly, we date the year of the move based on date 1 unless the inventor applied for a later non-semiconductor patent at firm A, in which case we use the year of that application as the year of the move, or if firm B entered later than date 1, in which case we use the year firm B entered as the year of the move. This year is referred to as the year of the observation.

We restricted our analysis to observations (A_1,B_2) where both patents were granted between 1970 and 2002 and patent A was applied for by 1987 or earlier (date 1 is based on the application date of patent A, which could be before 1970) in order to construct a sample with a sizable number of observations in the 1960s before the semiconductor industry was heavily clustered in Silicon Valley. We did not consider patents A_1 applied for after 1987 because our information on the origin of firms ended with entrants in 1987. We allowed patent B_2 to be granted as late as 2002 in order to allow for sufficient years to elapse to detect a change in employer. We have 7,879 observations in total involving 2,508 inventors, 279 of whom moved once, 27 who moved twice, and one who moved three times.

2.4 Broad Patterns

Before considering the mobility of inventors, we check how our dataset conforms to previous findings in the same industry. Table 2.1 reports the mobility rate of inventors in Silicon Valley[9] and elsewhere for various time periods. The mobility rate is

[9] An inventor is assumed to be at the location of the semiconductor operations of his employer. We checked this assumption by comparing the firm's location to the inventor's location reported in the patent filings. In almost all cases, the two locations were the same, and when not it was often due to an employer filing a patent in the inventor's name after he had moved to a new employer.

defined as the percentage of observations (A_1,B_2) in a time period for which firms A and B differ. Over all periods, the mobility rate was markedly higher for inventors in Silicon Valley than elsewhere — 9.1% versus 2.8%, or 3.2 times higher for Silicon Valley inventors.[10] This is consistent with Almeida and Kogut's (1999) findings for a smaller and less comprehensive sample of semiconductor patents and with qualitative evidence on the mobility of semiconductor workers in Silicon Valley (Saxenian 1994).

Curiously, the mobility rate of Silicon Valley inventors stands out for observations before 1971, when it equaled 13.8% versus 3.3% for inventors elsewhere. This is unexpected if the higher overall mobility rate in Silicon Valley was only the result of clustering, as the industry was much less clustered in Silicon Valley before 1971 than subsequently. Fallick et al. (2006) similarly questioned whether the higher mobility of college-educated computer workers in Silicon Valley was due to the clustering of the industry there. They found higher mobility not just in Silicon Valley but also throughout California, with mobility no greater in regions with a greater concentration of computer firms. They attributed their findings to California's ban on the enforcement of employee non-compete covenants rather than the clustering of the computer industry in Silicon Valley and elsewhere in California.

[10] This difference is significant at the .001 level based on Fisher's exact test.

Table 2.1: Mobility rate of inventors in Silicon Valley versus elsewhere.

	Overall			Before 1971			From 1971 to 1975			From 1976 to 1980			From 1981 to 1985			After 1985		
Region	Obs	Moves	Rate	Obs	Moves	Rate	Obs	Moves	Rate	Obs	Moves	Rate	Obs	Moves	Rate	Obs	Moves	Rate
Silicon Valley	1793	163	9.1%	109	15	13.8%	268	17	6.3%	353	23	6.5%	668	74	11.1%	395	34	8.6%
Other Regions	6086	173	2.8%	759	25	3.3%	1174	37	3.2%	1444	38	2.6%	1785	61	3.4%	924	12	1.3%
Total	7879	336	4.3%	868	40	4.6%	1442	54	3.7%	1797	61	3.4%	2453	135	5.5%	1319	46	3.5%
Ratio SV/Others			3.2			4.2			2.0			2.5			3.2			6.6

Table 2.2: Overall inventor mobility rate for firms with over 100 observations.

Company Name	Observations	Movements	Mob. Rate
Intel	236	27	11.4%
National Semiconductor	327	34	10.4%
Mostek	157	15	9.6%
Fairchild	346	31	9.0%
Signetics	227	17	7.5%
Advanced Micro Devices	290	16	5.5%
Harris	277	13	4.7%
Motorola	1575	48	3.0%
Raytheon Semiconductor	145	4	2.8%
Texas Instruments	1923	47	2.4%
RCA	1663	21	1.3%

Notes: Sample corresponds to all patents in five main IC classes granted between 1970 and 2002 to firms listed in the ICE database. Observations correspond to pairs of consecutive patents of the same inventor where the first patent was applied up to 1987. Moves correspond to observations where the assignees of the patents of an observation are different.

Our theory is that another factor might have contributed to the high early job mobility of Silicon Valley inventors — spinoffs. Between 1966 and 1970 Fairchild experienced a high rate of spinoffs, with three of the powerhouses of the industry, National, Intel, and AMD, founded by top employees of Fairchild in this period. Indeed, of the 15 moves out of 109 observations in Silicon Valley before 1971, 10 were accounted for by Fairchild's inventors. Six of the 10 involved moves from Fairchild to one of its spinoffs and two others involved a move from Fairchild to American Micro-Systems, which was founded by a prior Fairchild employee who had left Fairchild to co-found another Silicon Valley semiconductor firm, General Micro-Electronics (AMI's parent). Not surprisingly, the mobility rate at Fairchild before 1971 of 21.7% (10 moves out of 46 observations) was markedly greater than Fairchild's subsequent mobility rate of 7% (21 moves in 300 observations) and also markedly greater than the pre-1971 mobility rate of all other Silicon Valley firms of 7.9% (5 moves out of 63 observations).[11]

A broader indicator of the influence of spinoffs on mobility is conveyed by Table 2.2, which reports the overall inventor mobility rate at each of the 11 firms in our sample with at least 100 observations. The four firms with the highest mobility rates are, in order, Intel, National, Mostek, and Fairchild. As we noted, Intel, National, and Fairchild were all located in Silicon Valley and had the highest number of spinoffs among all the firms in our sample.[12] Perhaps even more telling is the other firm in the top four, Mostek, which was located in Dallas, TX. Its mobility rate of 9.6% was much higher than the mobility rate of inventors outside Silicon Valley of 2.8%. It was tied for the most spinoffs,

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[11] These differences are significant at the .01 and .05 levels respectively based on Fisher's exact test.

[12] Seeq was tied with National with three spinoffs on our list, but it entered much later and only had 24 observations. Its mobility rate, albeit on a small sample, was 20.8%, consistent with hypothesis 1.

two, of firms outside Silicon Valley, and 7 of its 15 moves were to its two spinoffs. All of these patterns are consistent with hypothesis 1a.

Hypothesis 2 and 3 are based on the idea that it will be harder for spinoffs outside of Silicon Valley to hire inventors away from local incumbents because they do not have many neighboring firms, and the most prominent firms out of Silicon Valley were also the larger and better established producers at the time. The three largest patenters in our sample by far are RCA, Texas Instruments, and Motorola, which were all large semiconductor producers that entered early in the industry (see Appendix A for detailed information on their patents). They were all located outside of Silicon Valley and had very low mobility rates. Conceivably the mobility rate outside of Silicon Valley was lower because RCA, TI, and Motorola were larger and had few spinoffs in relation to their size. RCA had the fewest spinoffs, with only one, and the lowest mobility among these firms. TI and Motorola had 3 and 2 spinoffs respectively and their mobility rate was about twice the rate of RCA. Among the rest of the firms outside Silicon Valley the mobility rate of inventors was 6.2% versus 2.2% for the inventors at RCA, TI, and Motorola.

We can analyze where the inventors came from that were hired by each firm, which bears on hypothesis 2. We consider three groups of firms: the three early major spinoffs from Fairchild, National, Intel, and AMD; the 34 later spinoffs in Silicon Valley with parents in our sample; and the seven spinoffs outside of Silicon Valley with parents in our sample. We distinguished National, Intel, and AMD from the later Silicon Valley spinoffs for two reasons. First, they entered when there were few firms to hire from in Silicon Valley other than their (common) parent, Fairchild. Although we argued Silicon Valley spinoffs could hire most of their initial workers locally, this would have been difficult for National, Intel, and AMD. Consequently, it might be expected that the

fraction of their hires from outside their region would be more comparable to the non-Silicon Valley spinoffs than the second group of later Silicon Valley spinoffs. Second, they were all founded within two years of each other, which might have limited the number of employees each could have hired from Fairchild. Consequently, they might be expected to be more like the later Silicon Valley spinoffs than the non-Silicon Valley spinoffs in terms of the fraction of hires from their parent.

Our hypotheses concern the initial hires of spinoffs. To operationalize the idea of initial hires, we consider the hires of firms in their first five years.[13] Among the 21 initial hires of National, Intel, and AMD, 33% were from Fairchild (their parent) and 21% of the others were from Silicon Valley firms. Among the 75 initial hires of the 34 later Silicon Valley spinoffs, 41% came from their parents and 68% of the others came from other Silicon Valley firms. Among the last group of seven spinoffs outside Silicon Valley, 52% of their initial 23 hires came from their parents, and 27% of the others came from firms in their region. Thus, as expected the early Silicon Valley spinoffs and the entrants outside Silicon Valley hired a greater percentage of their inventors from outside their region than the later Silicon Valley entrants. Consistent with hypothesis 2, the spinoffs outside Silicon Valley hired a greater percentage of their inventors from their parents when compared with spinoffs in Silicon Valley.

Last, we considered the 443 observations where the inventor of patent A_1 previously moved. Among these observations, the subsequent mobility rate was 3.3% (4 moves in 120 observations) for inventors who had previously moved to a spinoff of their

[13] In the various analyses we also experimented with adjusting the initial period by a year or two, which had little effect on our results.

parent and 7.7% for all the other inventors (25 moves in 323 observations).[14] These patterns are consistent with hypothesis 4.

2.5 Statistical Analysis

We begin with a simple accounting in Table 2.3 of the aggregate moves of inventors and the effect of these moves on the relative mobility of Silicon Valley inventors. Panel I of Table 2.3 reproduces Table 2.1, which reports the mobility rate of inventors in Silicon Valley and elsewhere in five-year intervals. To assess the relative importance of hypothesis 1a, we first take into account initial moves from parents to their spinoffs, which we again restrict to the first five years of the spinoffs. Panel II eliminates as moves all observations (A_1,B_2) in which firm B is a spinoff of firm A and date 1 is within five years of the entry of firm B. This reduces the mobility rate from 9.1% to 7.0% for inventors in Silicon Valley and from 2.8% to 2.6% for inventors elsewhere,[15] reflecting the much greater flow of inventors from parents to spinoffs in Silicon Valley than elsewhere. Consequently, the ratio of the overall mobility rate of inventors in Silicon Valley to inventors elsewhere falls from 3.2 to 2.6. Consistent with the discussion in Section 4, the biggest drop in mobility rates in Silicon Valley occurred in the period before 1971, when Fairchild was the source of most spinoffs and most inventor moves.

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[14] These percentages are not significantly different at the .05 level based on Fisher's exact test.

[15] For example, in Silicon Valley there were 163 observations out of a total of 1793 in which firm A and firm B were different (i.e., a move occurred). Of these, 38 involved cases where firm B was a spinoff of firm A and date 1 was within five years of the entry of firm B. Consequently, in panel II only 125 moves remain for Silicon Valley, which equal 7.0% of the original 1793 observations. The other entries in Panel II have been computed in the same way.

As stated in hypothesis 1b, Silicon Valley firms were also expected to have higher mobility due to a greater number of spinoffs from other local firms. In Panel III we remove all inventor moves to other local entrants (spinoffs or otherwise) in their first five years. Specifically, the number of observations (A_1,B_2) for which firm A and firm B are different but in the same region, firm A is not a parent of firm B, and date 1 is within five years of the entry of firm B are removed from the count of moves in each cell of Panel II. The mobility rate of Silicon Valley inventors falls from 7.0% to 4.4%, whereas the mobility rate of inventors elsewhere is hardly changed, which reflects that there were few local firms to move to except in Silicon Valley. The mobility rate of inventors in Silicon Valley relative to those elsewhere drops from 2.6 to 1.7. The drop is especially sharp before 1971, wiping out any difference between the mobility rates of the inventors in Silicon Valley and elsewhere.

Next we consider inventor moves to new entrants in other local areas that, according to hypothesis 3 are expected to occur at a comparable rate for all regions. This prediction, however, is not borne out in Panel IV, where we eliminate all moves where firm A and firm B are different and not in the same region, firm A is not a parent of firm B, and date 1 is within five years of the entry of firm B. The main reason is that a substantial number of inventors moved from firms outside Silicon Valley to Silicon Valley firms. This was especially true early on when the concentration of firms in Silicon Valley was lower and Silicon Valley firms had to go elsewhere to find inventors. Nevertheless, the mobility rate of inventors in Silicon Valley relative to inventors elsewhere in Panel IV of 2.0 is still lower than its value of 2.6 in Panel II. This indicates that entry overall had a bigger effect on the mobility of inventors in Silicon Valley than elsewhere, which is consistent with hypothesis 2.

Recall that the mobility rate of inventors at RCA, TI, and Motorola, the three largest patenters by far in the dataset, was especially low. If all observations (A_1,B_2) where firm A is either RCA, TI, or Motorola are removed from Panel IV (whether moves or not), the mobility rate of inventors outside Silicon Valley is 4.1%, which is nearly the same as the mobility rate of inventors in Silicon Valley. Thus, after eliminating all moves to recent entrants, the mobility rate of inventors in Silicon Valley is comparable to the mobility rate of all non-Silicon Valley inventors outside of the three largest patenters in the dataset, RCA, TI, and Motorola. This is consistent with our main argument, namely that most of the increased inventor mobility rate in Silicon Valley can be explained through the entry of spinoffs.

Paring various types of moves from the dataset is an accounting type of exercise, but we can also analyze inventor mobility econometrically, which provides a more exact way of testing our hypotheses. It also allows us to take into account various firm and inventor characteristics that might also affect the mobility of inventors. We pool the 7,879 observations (A_1,B_2) for all inventors and estimate a series of logit models in which the dependent variable is whether the inventor moved (i.e., firm B is different from firm A) and the explanatory variables include the number of recent spinoffs of firm A, the number of other recent entrants in firm A's region, the number of recent entrants outside of firm A's region, and whether the inventor was located in Silicon Valley. We also control for various features about the inventor and the inventor's firm (i.e., firm A), including the magnitude of patenting at the inventor's firm. Standard errors are computed by clustering the observations of each firm—i.e., all the observations of each firm A. Coefficient estimates are reported in Table 2.4.

Table 2.3: Accounting of inventor movements.

Panel I: Overall Mobility rates.

	Overall			Before 1971			From 1971 to 1975			From 1976 to 1980			From 1981 to 1985			After 1985		
Region	Obs	Moves	Rate	Obs	Moves	Rate	Obs	Moves	Rate	Obs	Moves	Rate	Obs	Moves	Rate	Obs	Moves	Rate
Silicon Valley	1793	163	9.1%	109	15	13.8%	268	17	6.3%	353	23	6.5%	668	74	11.1%	395	34	8.6%
Other Regions	6086	173	2.8%	759	25	3.3%	1174	37	3.2%	1444	38	2.6%	1785	61	3.4%	924	12	1.3%
Total	7879	336	4.3%	868	40	4.6%	1442	54	3.7%	1797	61	3.4%	2453	135	5.5%	1319	46	3.5%
Ratio SV/Others			3.2			4.2			2.0			2.5			3.2			6.6
Panel II: Excluding flows from parent to recent spinoffs.																		
Silicon Valley	1793	125	7.0%	109	9	8.3%	268	13	4.9%	353	18	5.1%	668	58	8.7%	395	27	6.8%
Other Regions	6086	161	2.6%	759	21	2.8%	1174	36	3.1%	1444	35	2.4%	1785	57	3.2%	924	12	1.3%
Total	7879	286	3.6%	868	30	3.5%	1442	49	3.4%	1797	53	2.9%	2453	115	4.7%	1319	39	3.0%
Ratio SV/Others			2.6			3.0			1.6			2.1			2.7			5.3
Panel III: Excluding flows to recent entrants in the same region.																		
Silicon Valley	1793	78	4.4%	109	3	2.8%	268	10	3.7%	353	15	4.2%	668	31	4.6%	395	19	4.8%
Other Regions	6086	158	2.6%	759	21	2.8%	1174	36	3.1%	1444	34	2.4%	1785	55	3.1%	924	12	1.3%
Total	7879	236	3.0%	868	24	2.8%	1442	46	3.2%	1797	49	2.7%	2453	86	3.5%	1319	31	2.4%
Ratio SV/Others			1.7			1.0			1.2			1.8			1.5			3.7
Panel IV: Excluding flows to recent entrants in other regions.																		
Silicon Valley	1793	71	4.0%	109	3	2.8%	268	10	3.7%	353	14	4.0%	668	28	4.2%	395	16	4.1%
Other Regions	6086	122	2.0%	759	13	1.7%	1174	29	2.5%	1444	30	2.1%	1785	41	2.3%	924	9	1.0%
Total	7879	193	2.4%	868	16	1.8%	1442	39	2.7%	1797	44	2.4%	2453	69	2.8%	1319	25	1.9%
Ratio SV/Others			2.0			1.6			1.5			1.9			1.8			4.2

Notes: Sample corresponds to all patents in five main IC classes granted between 1970 and 2002 to firms listed in the ICE database. Observations correspond to pairs of consecutive patents of the same inventor where the first patent was applied up to 1987. Moves corresponds to observations where the assignees of the patents of an observation are different.

The first model, Model 1, contains just one variable, denoted as *Silicon Valley*, which equals 1 if firm A in observation (A_1,B_2) was based in Silicon Valley and 0 otherwise. This serves as a benchmark for subsequent models. As expected, the coefficient estimate of *Silicon Valley* is positive and significant. It implies that the probability of moving relative to not moving is $e^{1.229} = 3.42$ times greater for inventors in Silicon Valley. This is close to the overall mobility rate of Silicon Valley inventors relative to non-Silicon Valley inventors in Table 3.1 of 3.2, which would be expected given that the probability of moving for any observation is close to 1.

Model 2 adds controls for characteristics of inventors and whether the inventor's firm is acquired. Palomeras and Melero (2010) found that inventors who were more central to IBM's mission were less likely to move to other firms. To measure an inventor's centrality to his firm, we include four variables denoted as *Tenure, Recent Patents*, *Co-inventors*, and *Self-Citations*. *Tenure* is the number of years between date 1 and the inventor's first patent at firm A in the sample, *Recent Patents* is the number of patents of the inventor at firm A in the three years before date 1, *Co-inventors* is the average number of co-inventors at firm A on the inventor's past patents at firm A, and *Self-citations* is the percentage of citations (in other patents) to the inventor's past patents at firm A through 2002 by firm A itself.[16] To test if acquired firms have greater inventor turnover, which might be expected if acquisitions lead to consolidations and changes in firm strategies (Ernst & Vitt 2000), we include a dummy variable, *Acquisition*,

[16] Citations were obtained from the NBER patent citations database. As this database only contains citations to patents granted from 1976 onward, we supplemented it with all the citations made by the patents in our database that were granted before 1976.

equal to 1 if firm A was acquired within three years of date 1 and 0 otherwise. This variable is also interacted with the variable *Recent Patents* to test if acquisitions particularly increase the turnover rate of less productive inventors. Last, *Prior Move*, which equals one if the inventor moved prior to the patent at firm A and 0 otherwise, is included to test whether prior movers are more likely to move again. A priori, the sign of this coefficient could go either way depending on the fraction of prior movers who would not move again because they are more productive at their new employer.

The coefficient estimates reported under Model 2 all have the expected signs, and a number are significant. The longer the inventor's tenure at firm A, the more patents the inventor recently assigned to firm A, the greater the number of co-inventors on the inventor's patents at firm A, and the greater the self-citation rate to the inventor's patents at firm A, then the less likely the inventor is to leave firm A, with the effects of all but *Tenure* significant. Inventors whose firms are acquired are more likely to move, particularly less productive inventors, although neither effect is significant. Last, the coefficient estimate of *Prior Move* is positive, suggesting that inventors who moved once were more likely to move again than other inventors, although it is not significant. The addition of these variables causes the coefficient estimate of *Silicon Valley* to fall to 0.999, which implies that the probability of moving relative to not moving is 2.72 times greater for inventors in Silicon Valley. This decline reflects that on average the number of recent patents, the percentage of self citations, and firm tenure were lower for inventors in Silicon Valley than elsewhere.

Hypothesis 1a says that mobility of a firm's inventors will be directly related to the number of recent spinoffs it spawned. We again allow for up to five years for the firm to complete its initial hires. Accordingly, in Model 3, for each observation (A_1,B_2) we add a

variable, denoted as *Number of Spinoffs*, equal to the number of spinoffs of firm A in the five years before date 1. As expected, the coefficient estimate of *Number of Spinoffs* is positive and significant. It implies that for each additional spinoff a firm spawns, the probability of its inventors moving relative to not moving increases by 28.5% during the first five years of the spinoff. The coefficient of *Silicon Valley* falls to 0.727, reflecting that part of the higher mobility of inventors in Silicon Valley is due to a greater incidence of spinoffs hiring inventors from their parents in Silicon Valley than elsewhere. The reduction in the coefficient estimate implies that the probability of moving relative to not moving is now 2.07 times higher for inventors in Silicon Valley, which is not far from the relative mobility rate of 2.6 in Panel II of Table 2.3 after we eliminated all moves from parents to their recent spinoffs.

Hypothesis 1b states that the mobility of a firm's inventors will also depend on the number of recent spinoffs spawned by neighboring firms. This is much more difficult to test econometrically. There was little entry outside Silicon Valley; thus it is only feasible to analyze how entry in Silicon Valley affected inventor mobility. Accordingly, for each observation (A_1,B_2) we constructed a variable, denoted as *Number of SVEntrants*, which equals the number of entrants in Silicon Valley in the five years prior to date 1 other than the firm itself and its spinoffs.[17] Unfortunately, unlike the variable *Number of Spinoffs*, there is virtually no cross sectional variation in the variable *Number of SVEntrants*. Consequently, its estimated effect largely works off the correlation over the years spanned in our sample of average inventor mobility in a region and the rate of entry in Silicon

[17] This variable includes all entrants, not just spinoffs, in Silicon Valley, although nearly all the entrants there were spinoffs.

Valley. Not only is this not a lot to go on, but we also had to impose a dating on moves that is inexact and thus likely to introduce further complications.

Table 2.4: Estimates for likelihood of inventor move to another firm.

Logit:	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Silicon Valley	1.229***	0.999***	0.727***	0.451*	0.609	0.612*	0.207
	(0.215)	(0.196)	(0.217)	(0.270)	(0.371)	(0.369)	(0.423)
Tenure		-0.032	-0.031	-0.032	-0.034	-0.034	-0.026
		(0.021)	(0.021)	(0.021)	(0.023)	(0.023)	(0.021)
Recent Patents		-0.412***	-0.404***	-0.403***	-0.404***	-0.401***	-0.365***
		(0.078)	(0.076)	(0.075)	(0.075)	(0.075)	(0.072)
Co-inventors		-0.101	-0.110	-0.119	-0.131**	-0.130**	-0.094
		(0.079)	(0.077)	(0.076)	(0.066)	(0.066)	(0.065)
Self-citations		-0.018***	-0.020***	-0.019***	-0.019***	-0.019***	-0.018***
		(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Acquisition		1.037	1.039	1.076	1.073	1.092	0.960
		(0.816)	(0.858)	(0.853)	(0.855)	(0.862)	(0.801)
Acquisition * Recent Patents		-0.560	-0.614	-0.607	-0.610	-0.617	-0.620
		(0.664)	(0.692)	(0.682)	(0.680)	(0.683)	(0.630)
Prior Move		0.148	0.240	0.232	0.222	0.283	0.221
		(0.243)	(0.235)	(0.229)	(0.226)	(0.256)	(0.237)
Number of Spinoffs			0.251***	0.261***	0.265***	0.263***	0.344***
			(0.040)	(0.047)	(0.048)	(0.048)	(0.052)
Number of SVEntrants*SV				0.022	0.022	0.022	0.032**
				(0.014)	(0.014)	(0.014)	(0.013)
Number of SVEntrants*(1-SV)					0.014	0.014	0.023
					(0.024)	(0.024)	(0.019)
Movers from Parent to Spinoff						-0.374	-0.699
						(0.485)	(0.510)
Log(Firm patents)*SV							-0.363***
							(0.084)
Log(Firm patents)*(1-SV)							-0.335***
							(0.088)
Constant	-3.532***	-2.197***	-2.236***	-2.222***	-2.363***	-2.366***	-1.208***
	(0.188)	(0.285)	(0.292)	(0.293)	(0.446)	(0.446)	(0.393)
Observations	7879	7879	7879	7879	7879	7879	7879
Pseudo R2	0.040	0.099	0.105	0.106	0.106	0.106	0.120
Log Lik	-1333	-1252	-1243	-1242	-1242	-1241	-1222

Std. Errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Notes: Sample corresponds to all patents in five main IC classes granted between 1970 and 2002 to firms listed in the ICE database. Observations correspond to pairs of consecutive patents of the same inventor where the first patent was applied up to 1987. Dependent variable is dummy equal to 1 if the assignees of patents are different in observation. All variables are measured with respect to the first patent of the observation (assignee and time of application).

Subject to these caveats, in Model 4 we begin by allowing *Number of SVEntrants* to affect the mobility only of inventors in Silicon Valley, which is achieved by entering *Number of SVEntrants* times the 1-0 dummy variable *SV*, which equals 1 if firm A in observation (A_1,B_2) is in Silicon Valley. Consistent with hypothesis 1b, the coefficient estimate of *Number of SVEntrants*SV* is positive, although it is not significant. It implies that each additional entrant in Silicon Valley increased the probability of moving relative to not moving of inventors at other Silicon Valley firms during the entrant's first five years by 2.2%. This is smaller than the effect of an additional spinoff on the mobility of inventors at the spinoff's parent, as would be expected. The coefficient estimate of *Silicon Valley* drops sharply and is now only significant at the 10% level, reflecting that a substantial part of the higher mobility of inventors in Silicon Valley is due to the greater incidence of spinoffs hiring inventors from local firms (other than their parents) in Silicon Valley than elsewhere.[18]

In Model 5 we multiply *Number of SVEntrants* by (1 – *SV*) to allow entry in Silicon Valley to affect the mobility of inventors elsewhere. This is not something we addressed in our theoretical framework, but it was certainly important early on when the number of firms and inventors in Silicon Valley was small. The coefficient estimate of this variable is positive but not significant and is smaller than the coefficient estimate of *Number of SVEntrants*SV*.[19] The addition of this variable increases the coefficient

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[18] We also experimented with expressing the number of entrants in Silicon Valley relative to the number of incumbents in Silicon Valley based on the logic that the effect of each additional entrant will be smaller the larger the number of inventors in Silicon Valley. The coefficient estimate of this version of the variable was positive but not significant, which may reflect that the number of incumbents is not a good measure of the number of inventors in Silicon Valley.

[19] Comparing the coefficients in this manner is tricky because model 5 is equivalent to specifying an interaction between the dummy variable *Silicon Valley* and the variable *Number of SVEntrants* (with the

estimate of *Silicon Valley*, although it is no longer significant. It implies that the probability of moving relative to not moving is 1.83 times higher for Silicon Valley inventors.

Hypothesis 4 states that among inventors who moved, those who moved from a parent to spinoff would be less likely to move again. To test this, in Model 6 we include a variable, denoted as *Movers from Parent to Spinoff*, which equals 1 for observations of inventors who previously moved from a parent to one of its spinoffs. The coefficient estimate of *Movers from Parent to Spinoff* is negative, consistent with hypothesis 4, but it is not significant.

Last, in Model 7 we control for the log of the number of patents issued to firm A in the year before the observation (plus 1 to accommodate firms with no prior patents), which would be expected to influence negatively the mobility rate at firm A. We allow this variable, denoted as *Log(Firm patents)*, to have a separate effect for Silicon Valley and non-Silicon Valley firms to test whether size affects mobility differently across regions. This is particularly relevant given the importance of TI, RCA, and Motorola outside of Silicon Valley. The coefficient estimates of both variables are negative, significant, and quite close in magnitude, supporting the idea that the mobility of inventors is lower at larger firms. When these variables are included, the coefficient estimate of *Silicon Valley*

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latter allowed to affect inventors at all firms), and interaction effects in non-linear models depend on the values of the explanatory variables in complex ways (Ai & Norton 2003). To circumvent this awkwardness, we estimated Model 5 (and 6) as linear probability models. The coefficient estimate of the number of Silicon Valley entrants for inventors in Silicon Valley was about three times as large as that for inventors elsewhere, as would be expected based on the logic of hypothesis 2, although neither coefficient estimate was significant. The coefficient estimate of *Silicon Valley* implied a roughly two times higher mobility of inventors in Silicon Valley than elsewhere, although it too was not significant. The rest of the coefficient estimates and their significance were comparable to the logit coefficient estimates.

drops to 0.207, which implies a probability of moving relative to not moving of 1.23, and is no longer significant. This is consistent with our earlier finding that, excluding RCA, TI, and Motorola, the mobility rates of inventors in Silicon Valley and elsewhere are virtually the same after accounting for moves from parents to their recent spinoffs and other recent entrants. Controlling for firm size also causes the coefficient of *Number of SV Entrants* for Silicon Valley inventors to become larger and significant, consistent with hypothesis 1b.

We report one further analysis of the labor flows among semiconductor firms. We argued that recent entrants hired their initial staff mainly from incumbents. An interesting question is how incumbents replace the inventors they lose. Angel (1989) found on his survey of semiconductor engineers that large incumbents do not usually rely on external sources to hire inventors from. Instead, they hire mostly recent graduates and have organized internal labor markets. Accordingly, the oldest and largest firms in our sample should have lost the most workers to entrants but not replaced them with workers from other firms in our sample. For each of our firms that lost 10 or more employees to other firms in the sample, Table 2.5 reports the gross number of inventors they lost and the number they hired from the other firms in their first five years (after entry), as well as in subsequent years.

The patterns in Table 2.5 largely conform to our argument. The top six firms in terms of gross outflow of workers are TI, Motorola, Fairchild, and RCA, which were all early entrants and (at some point) large firms. The inflow of workers into these firms (which occurred after these firms' first five years in the industry) mostly involved inventors with no prior patents. The other two firms with a large gross outflow of inventors were the top two early Silicon Valley spinoffs, National and Intel. As would be expected, the majority of their hires in their first five years came from other ICE firms in

our sample, and few of their inventors were hired by other firms, whereas subsequently their hires mainly involved individuals with no prior patents and they start losing many inventors to other firms. The outflow from AMD, the other early leading Silicon Valley spinoff, was more modest and its net inflow unexpectedly large. However, AMD was not particularly successful at first, capturing only 1.5% of the sales of the ICE firms five years after it entered. Its market share grew later to 8.2% after Intel chose it as its official second source for microprocessors. Consequently, it built up its workforce well after it entered, which limited the number of workers hired by other firms from AMD. Last, the firms grouped together at the bottom of Table 2.5 were largely later spinoffs. As would be expected, initially they hired many more inventors than they lost to other firms, with the majority of these inventors hired from other ICE firms in our sample. Subsequently they hired more inventors without prior patents and lost more inventors to other ICE firms in our sample.

2.6 Robustness Tests

We performed a series of robustness tests of our estimates. First, we explore if observations where there is a long time between consecutive patents of an inventor could introduce any bias in the results. We then explore whether focusing in movements to a restricted set of firms could drive our results, and also test an alternative specification of the model. Finally, by exploiting variations between Silicon Valley and other regions as well as temporal variations in the level of concentration of the industry, we explore the effect of increasing clustering over our results.

Table 2.5: Number of inventors hired away from and by the leading sources of inventors.

	Movements between ICE firms				Inventors with no prior patents		Inventors from other firms			
	Outflow		Inflow				w/o IC Patents		w/ IC patents	
Company Name	First 5y	After 5y	First 5y	After 5y	First 5y	After 5y	First 5y	After 5y	First 5y	After 5y
Texas Instruments	---	47	---	10	---	548	---	6	---	6
Motorola	---	48	---	24	---	512	---	11	---	13
National Semiconductor	3	31	10	29	9	91	0	2	0	7
Fairchild -Schlumberger	---	31	---	11	---	117	---	2	---	6
Intel	0	27	6	23	4	97	0	0	2	6
RCA	---	21	---	3	---	412	---	5	---	3
Signetics -Philips	---	17	---	11	---	77	---	2	---	4
Advanced Micro Devices	0	16	5	29	0	98	0	4	0	7
Mostek -UTC/ST	0	15	3	9	2	36	0	1	0	3
Harris	0	13	0	3	0	86	0	3	2	3
General Instrument	---	10	---	5	---	35	---	0	---	0
All other firms	9	48	119	36	50	215	4	2	4	9

Note: All firms with --- in the first five years fields entered in a period where we do not have information on patents.

Table 2.6: Estimates for likelihood of inventor move to another firm, robustness checks.

Logit:	Model 8 (Pat. Gap)	Model 9 (Extended)	Model 10	Model 11	Model 12	Model 13
Silicon Valley	0.113	0.086	0.223	0.210	0.380	
	(0.475)	(0.346)	(0.434)	(0.450)	(0.456)	
Silicon Valley * Up to 75						0.151
						(0.444)
Silicon Valley * From '76						0.339
						(0.448)
Number of Spinoffs	0.371***	0.159***			0.339***	0.349***
	(0.075)	(0.046)			(0.055)	(0.054)
Number of Spinoffs * SV			0.339***			
			(0.050)			
Number of Spinoffs * (1-SV)			0.391	0.390		
			(0.298)	(0.297)		
Number of Spinoffs * SV * Up to '75				0.349***		
				(0.059)		
Number of Spinoffs * SV * From '76				0.333***		
				(0.059)		
Number of SVEntrants * SV	0.043**	0.017	0.032**	0.033**		0.025*
	(0.020)	(0.011)	(0.013)	(0.016)		(0.013)
Number of SVEntrants * (1-SV)	0.021	0.004	0.024			0.024
	(0.028)	(0.017)	(0.022)			(0.019)
Number of SVEntrants * SV * Up to '75					-0.000	
					(0.045)	
Number of SVEntrants * SV * From '76					0.026**	
					(0.012)	
Number of SVEntrants * (1-SV) * Up to '75					0.039	
					(0.036)	
Number of SVEntrants * (1-SV) * From '76					0.027	
					(0.020)	
Tenure, Recent Patents, Co-Inventors, Self-Citations, Acquisition, Acquisition * Recent Patents, Prior Move, Movers from Parent to Spinoff, Log(Firm Patents) * SV, Log (Firm Patents) * (1-SV)						
Constant	-1.960***	-0.817**	-1.220***	-1.221***	-1.269***	-1.204***
	(0.394)	(0.344)	(0.406)	(0.406)	(0.413)	(0.393)
Observations	7347	8340	7879	7879	7879	7879
Log Lik	-897.4	-2287	-1222	-1222	-1222	-1222
Pseudo R2	0.095	0.105	0.120	0.120	0.120	0.120

Notes: Robustness tests of models presented in Table 2.4. Model 8 (Patent gap test) is the analogous of Model 7, but eliminating observations for which more than 6 years elapsed between the application of the first and second patent. Model 9 (Extended sample test) is the analogous of Model 7, but allowing the second patent to be at any firm (not just at firms listed in the ICE database). Models 10-13 are based on the original sample and add additional coefficients to explore implication of temporal and regional differences.

When there was a long period between consecutive patents of an inventor, dating moves and measuring variables based on the year of the first patent is likely to be more suspect. Accordingly, we estimated the seven models excluding observations for which the number of years between consecutive patents was greater than six. For the sake of brevity only the analog of Model 7 is presented as Model 8 in Table 2.6. We call this model the patent gap test. The resulting estimates are now even more in line with our hypotheses. In particular, the number of entrants in Silicon Valley now has a significant positive effect for inventors in Silicon Valley in all models and is over twice as great as the analogous coefficient estimate for inventors elsewhere, which is always insignificant. Furthermore, the coefficient estimate of the Silicon Valley dummy is now smaller and insignificant, when compared to Models 4 to 7.

Another concern with our specification is that exploring movements of inventors between specific firms could hide other features of the process. To address this we reestimated all seven models allowing inventors to move to any firm, not just semiconductor firms in our sample (i.e., the second patent, B_2.in any observation could be at any firm). We call this an extended sample test. Although this adds many movements that cannot be explained by our variables, the results remained qualitatively the same, as reported in Model 9 in Table 2.6. Finally, we also redefined observations so that every year between an inventor's first and last patent (up to 1987) was considered a separate observation, with the dating of moves unchanged. This too did not qualitatively change our results (but as might be expected, standard errors of the estimates declined due to the increase in number of observations).

The empirical analysis presented in section 5 supports the view that spinoffs draw many inventors from their parents and other local firms during their first years, and that these movements account for a significant fraction of the excess mobility in Silicon Valley.

What is harder to determine is how the clustering of the industry in Silicon Valley determined the availability of inventors and how this affected spinoffs' hiring choices. Hypothesis 2 states that spinoffs in Silicon Valley could rely less on their parents to hire their initial staff, as they could hire workers from other local firms. Statistically testing this hypothesis is challenging because most entry was concentrated in Silicon Valley. Of the 81 firms in the ICE listing that had patents, 53 were spinoffs of other ICE listed firms. These spinoffs came from 19 parents, 14 of which were located in Silicon Valley and spawned 43 firms. The 5 parents located in other regions spawned 10 firms. While it would be difficult to obtain statistically significant estimates with this variation, we attempted to estimate the *Number of Spinoffs* coefficient separately for firms in and out of Silicon Valley. Model 10 in Table 2.6 shows that the coefficient of *Number of Spinoffs* is larger for firms out of Silicon Valley than for firms in Silicon Valley, although is not significant. This result is in line with the idea that spinoffs out of Silicon Valley rely more heavily on their parents to hire inventors from than spinoffs elsewhere, which was the basis for hypothesis 2.

The differences we find between firms located in and out of Silicon Valley seems at odds with previous literature on the effects of non-compete covenants over inventor mobility. The inability of enforcing non-compete agreements in Silicon Valley is believed to have faciliated the mobility of inventors and the clustering of the industry there (Fallick et al. 2006; Gilson 1999; Marx et al. 2009). Semiconductor firms in Silicon Valley should be more able to hire workers from their parents than firms elsewhere (i.e., outside of California), which is the opposite of what we find. This can be explained if non-compete agreements are not perfect in preventing worker mobility. If the founder was able to leave to create an spinoff, he must have found a way to circumvent the non-compete, or the parent simply wasn't interested in enforcing the agreement. If the non-compete didn't

prevent the founder from leaving, it is reasonable to assume it will not prevent additional workers from leaving to join the spinoff. The patterns observed in our data suggest that non-competes may hinder the rate at which spinoffs are generated, but conditional on entry they will have no effect on preventing movements from parent to spinoff. Given the importance of spinoffs in fostering mobility and knowledge diffusion in Silicon Valley, determining specifically how non-competes prevented firm entry in other regions is an interesting research question.

Besides exploiting the differences between Silicon Valley and other regions we can also attempt to gain some insights from exploring temporal variations. In the early years of our sample the industry was less concentrated in Silicon Valley. Up to 1975 there were 20 spinoffs entrants, 14 of them in Silicon Valley and 6 in other regions. After 1975 there are 33 spinoffs entrants, of which 29 are in Silicon Valley and 4 elsewhere. In Model 11 of Table 2.6 we estimate the *Number of Spinoffs * SV* coefficient separately for spinoffs that enter up to 1975 and for those that enter later. While we can't reject the hypothesis that both coefficients are equal, the coefficient of the earlier period is larger. This would be consistent with the idea that, when the industry was less clustered in Silicon Valley, spinoffs had to rely more on their parents to hire their initial staff. Model 12 of Table 2.6 estimates the effect of *Number of SV Entrants* over mobility in firms in and out of Silicon Valley, allowing the coefficients to vary before and after 1975. Up to 1975, the coefficient of the effect of entry in Silicon Valley over firms in Silicon Valley is the smallest among the firm entry coefficients, while the coefficient of the effect over firms out of Silicon Valley is the largest. After 1975 the coefficients for firms in and out of Silicon Valley become similar. Although the only combination that is statistically significant is the coefficient of *Number of SV Entrants * SV * From 1976,* these results provide an interesting insight. They imply that, when the industry had not yet clustered in Silicon

Valley, spinoffs entering there had to attract experienced inventor from other regions. Finally, in Model 13 of Table 2.6 we experimented with the *Silicon Valley* dummy coefficient, estimating it separately for up to 1975 and later. The coefficient of the earlier period is smaller, which would indicate that as the industry clustered inventor mobility increased, although both dummies are not significant.

2.7 Implications about Agglomeration Economies

Inventor mobility figures prominently in the literature on industry agglomeration. According to this literature, when firms in an industry cluster geographically, it is less costly for workers to change jobs, which leads to greater worker mobility. In turn, greater mobility can improve the match between the skills of employees and the needs of heterogeneous employers, increasing worker productivity (Helsley & Strange 1990; Duranton & Puga 2004). Greater worker mobility can also speed up the diffusion of knowledge across firms (Almeida & Kogut 1999; Breschi & Lissoni 2007), making it easier for co-located firms to keep up with the technological frontier in their industry. These benefits, which have been dubbed agglomeration economies, impart a self-reinforcing character to industry agglomerations (Duranton & Puga 2004). In this section we explore how our findings relates to previous works about agglomeration economies.

Labor pooling is one of the ways firms may benefit from being located in a cluster. Having many job seekers and hiring firms in a concentrated area may increase the quality of the match between employers and employees, improve the chances of finding suitable matches, and mitigate hold-up problems (Duranton & Puga 2004). Models that explain how these benefits materialize rely on inventor mobility to different extents. In the analysis presented in section 5, we noted that most of the additional flows of inventors that occur in Silicon Valley appear to be due to workers moving to recent (spinoff)

entrants. If the benefits of labor pooling depend on the mobility of workers to materialize, the patterns we find suggest that new firms will disproportionately benefit from labor pooling. For example, the model on matching of Helsley and Strange (1990) is based on the idea that firms may increase the overall quality of the match between their needs and their workers' skills by hiring good matches from competitors. This leads to an increase in overall productivity due to labor market competition. Our results suggest that this mechanism would operate mainly through spinoffs hiring the inventors that suit their needs from their parents and other incumbents. As such, incumbents would realize little benefits through this mechanisms from being located in a cluster.

While incumbents would see few additional benefits from mechanisms that materialize through inventor mobility, they still may get other gains from remaining in the cluster. Models that explain increases on the probability of finding a good match due to clustering are based on matching functions that depend on the number of job seekers, and of positions available (Duranton & Puga 2004). The key advantage of clusters in these models is the variety of workers available. While incumbents may not be firing and hiring experienced inventor more frequently in clusters, when they do they may gain from having a more diverse pool of workers to choose from. Spinoffs may actually strengthen this mechanisms by attracting workers to the cluster who will add further variety to the pool of potential hires.

Incumbents may also benefit in a less obvious way from labor pooling. In a survey of engineers from the semiconductor industry, Angel (1989) finds that larger organizations hired many engineers right out of college. We do not have information on how many of these engineers stay with their initial employers. Nonetheless, models of labor turnover propose that when the abilities of workers are uncertain, as it is in the case of hiring new graduates, firms hire many employees and only retain those that are good fits (Jovanovic

1979; Topel & Ward 1992). Following this logic, incumbents located in a cluster will be attractive for newly graduates for the employment opportunities that exist in the region, many of which will be at new (spinoff) entrants.

Worker mobility also figures prominently in the literature on agglomeration economies as a channel for knowledge spillovers. Models on knowledge spillovers through worker mobility start from the assumption that valuable and non-codifiable knowledge is embedded in employees. Competitors wanting to acquire this knowledge may hire these workers in order to access it. Firms located in clusters benefit from learning through labor pooling, but also suffer the costs of knowledge leaks associated with labor poaching. Models like Cooper (2001) and Combes and Duranton (2006) find conditions where high labor mobility may be beneficial for co-located firms. These models propose that there exists an equilibrium between the gains achieved by acquiring knowledge through hiring experienced workers and the costs imposed by losing workers due to labor poaching. Our results suggests that the cost of labor poaching are being suffered by incumbents while the benefits of labor pooling are reaped by spinoffs, which makes the equilibrium proposed by these models difficult. Nevertheless, incumbents may still benefit from knowledge spillovers that materialize through other channels, such as spillovers that occur thanks to frequent interaction (von Hippel 1987), or a more open culture in Silicon Valley (Saxenian 1994), important complementary aspects that our work does not directly address.

The literature on agglomeration economies presented in this section features clustering as having a direct and homogenous effect on worker mobility. As such, the heightened job mobility resulting from clustering should hold for all workers and will persist for workers in Silicon Valley even after taking into account the effect of spinoffs and other firm influence on job mobility. Yet, the empirical evidence presented in this paper suggests that most of the extra mobility observed in Silicon Valley is due to the

entry of spinoffs. This leads us to believe that the greater availability of workers in Silicon Valley promotes spinoff formation, and the initial hiring that takes place at new firms raises inventor mobility in the region.

Fully determining if agglomeration economies raises worker mobility at all firm, or if it promotes mobility by facilitating the entry of new ventures is challenging. The key question is whether agglomeration economies are spurring spinoff entry by themselves, or if they are facilitating spinoff entry that was motivated by an exogenous factor. If spinoffs are the result of firms' limited ability to judge new ideas, as featured in Klepper and Thompson's (2010) model of spinoffs, and clustering just makes it easier for employees to form a spinoff to pursue ideas neglected by their employers, then the role of agglomeration economies would be mostly indirect. Their role would be direct if they raise the rate of generation of spinoffs ideas, for example, through peer effects (Nanda & Sørensen 2010), cross-fertilization of ideas that result from the interaction of diverse firms (Jacobs 1969), or through demand pull resulting from the rise of the venture capital industry there (Kenney & Florida 2000). Whether spinoff entry is directly or indirectly affected by agglomeration economies is an interesting and challenging research question, but it is beyond the scope of this paper. Whatever the reason for spinoff entry is, the basic tenet of our theory holds. Spinoff entry raises regional mobility rates, and most of the increased labor mobility in Silicon Valley is the result of inventors moving from incumbents to young firms.

2.8 Discussion

In this paper we systematically analyze the mobility of inventors in the semiconductor industry during the period where the industry was becoming increasingly clustered in Silicon Valley. We develop a theoretical framework of how spinoffs hire their

initial workforce from their parents, from other local firms, and if needed from non-local firms. If spinoffs hire many inventors from their parents, as featured in our theory, the greater rate of firm entry in Silicon Valley could explain the higher mobility of inventors there. Our theory also explores how the availability of inventors could affect spinoffs' hiring choices. The reliance of spinoffs on their parents will diminish as the availability of trained inventors from other local firms increases.

Hiring patterns and mobility rates of inventors that consistently patented in the main semiconductor classes at the ICE firms generally conformed to our hypotheses. Silicon Valley spinoffs initially hired a smaller percentage of their inventors from their parents and a greater percentage of their inventors locally (especially after 1970) than spinoffs elsewhere. Inventors had the highest mobility rate at firms that spawned the most spinoffs, which were predominantly located in Silicon Valley. Mobility rates of inventors were highest at firms around the times they spawned their spinoffs and when spawning rates of other local firms were high. Inventor moves from parents to spinoffs and from incumbent firms to entrants accounted for over half of the greater mobility of inventors in Silicon Valley.

Our methodology for analyzing the mobility of semiconductor inventors has a number of limitations that should be considered. First, it restricts moves to those between merchant ICE firms and does not capture moves to captive semiconductor producers, lesser semiconductor firms, or non-semiconductor producers. However, apart from AT&T and IBM, which were large captive producers, our firms represent all the major semiconductor innovators in the era we study and thus the firms accounting for most of

the flows of inventors.[20] Second, we cannot capture flows in which inventors do not patent at both the source and destination firms. This is common to all studies of employee mobility that use patent data. It is not clear how, if at all, this might affect our conclusions. Last, the timing of mobility is based on a rule that cannot precisely date every move. While we recognize that these rules are somewhat arbitrary, some kind of designation for time periods is necessary for us to identify a firm's formative period and the timing of inventor moves.

Our main conclusion is that the higher rate of spinoff entry in Silicon Valley was of primal importance in driving the higher mobility of inventors there. This is an intriguing result, as it questions how and to what extent clustering and the ban on the enforce of non-compete agreements foster mobility in the region. Some of the patterns we find seem inconsistent with the idea that these mechanisms are the sole reason for the prevailing job hopping in Silicon Valley. On one hand, inventor mobility in this region was higher early on, when there weren't many semiconductor firms in the region and thus the cluster effect would not be particularly significant, especially in comparison to certain regions in the East coast. On the other hand, the enforceability of non-compete agreements outside of the state of California should make hiring inventors away from parents harder for spinoffs located in those regions. This is the opposite of what we find, as spinoffs outside of Silicon

[20] We excluded captive producers from our analysis for two reasons. First, we do not have a way of comprehensively identifying captive producers. Second, we anticipated that during the era we studied captive producers, including AT&T and IBM, were not directly competing with merchant semiconductor producers and thus their inventor mobility patterns would be different from the firms in our sample. Indeed, Bassett (2002, p. 223) noted that while the semiconductor industry was famous for its mobility, after 1964 no person came to a position of responsibility in IBM's semiconductor operations from another firm. Consistent with this observation, although IBM was issued many semiconductor patents, we found only six instances of inventors in our sample moving to IBM. We also found only six inventors in our sample moving to AT&T as well even though it was also a major semiconductor patenter, suggesting it too was atypical of the firms in our sample.

Valley hired more inventors from their parents than spinoffs in Silicon Valley. These patterns do not rule out that agglomeration and the ban of non-compete agreements in California influenced the rate of spinoffs' entry, which they certainly did. Rather, they highlight the importance of the spinoff process in driving inventor mobility, even in the absence of any regional advantages.

Existing studies of inventor mobility and patent citations suggest that hiring inventors provides a way for firms to access the knowledge of their prior employers (Almeida et al. 2003; Rosenkopf & Almeida 2003; Kim & Marschke 2005; Tzabbar 2009; Singh & Agrawal 2011). Our interpretation of the greater mobility of inventors in Silicon Valley implies that the benefits of such hiring were reaped disproportionately by entrants. This is consistent with Sørensen and Stuart's (2000) finding that younger firms are more likely than older rivals to exploit external knowledge. It could also help explain the finding of Almeida et al. (2003) that inventor mobility in the semiconductor industry disproportionately benefits hiring firms that are small, which will tend to be recent entrants. If entrepreneurial firms are disproportionately benefiting from knowledge acquired through inventor mobility, conceivably this comes at the cost of the incumbents who unwittingly serve as training grounds for the initial employees of spinoffs. This is consistent with Agarwal et al. (2009), who find that larger firms in the semiconductor industry are very zealous in protecting their IP in order to build a reputation of being "tough" in patent enforcement, which ultimately has an effect in reducing knowledge flows that result from inventors moving to smaller and younger firms.

Our results have important implications for public policy and business strategy. It is often argued that clustering promotes job mobility and the diffusion of knowledge among all firms in clusters, enabling them to be closer to the technological frontier in their industry. This is a classic agglomeration economy externality that can justify public

policies to promote clusters and also motivate incumbents to relocate in clusters. Alternatively, our results suggest that spinoffs rather than incumbents realize the benefits related to the higher rate of labor mobility there. Clustering of the industry in Silicon Valley may have made entry more attractive there by making it easier for entrants to hire their initial labor force (cf. Glaeser & Kerr 2009; Alcácer & Chung 2007), but this advantage becomes less relevant as the firm becomes established and its need for trained workers diminishes. If this is the case, it is intriguing how spinoffs consider this in their location decision. While being located in a cluster could pose problems for the spinoff in the future, locating in another region could significantly hurt its chances of survival. The spinoff may prefer to locate in the cluster and take advantage of its regional knowledge and the availability of inventors, even if this will cause higher costs in the future if the firm is successful.

Combes and Duranton (2006) reflect the disadvantages of established firms in clusters in their model of firm location and worker hiring. In the model, the only way to tap into the technology of other firms is through hiring their workers, which is facilitated by being located in a cluster. But firms in clusters also have more difficulty keeping their workers and technology. Co-location is socially optimal in the model, but the more intense competition is among firms, as reflected in the degree of substitutability of their products, the more firms do not co-locate. This was not borne out by spinoffs of Silicon Valley firms, which did not stray far from their geographic roots. This may reflect the fact that spinoffs' knowledge is limited, and thus concerns about losing workers to rivals are less important than being able to hire experienced labor from their parents,[21] which

[21] Consistent with this conjecture, Alcácer and Chung (2007) find that among foreign entrants into the U.S., those that were less technologically advanced were more likely to locate close to other firms in their industry.

would presumably be more difficult if they did not locate close to them (and their workers).[22] Incumbent firms also did not move over time away from Silicon Valley, as Combes and Duranton's (2006) model might suggest. We suspect this also had to do with (retaining) their labor force, which is consistent with Alcácer and Chung's (2009) findings concerning the importance of skilled labor in the location choice of foreign entrants into the U.S.

If being located in Silicon Valley was not advantageous to incumbents, this would help explain the long-time success of TI and Motorola, both of which were located far from Silicon Valley. It calls into question, though, why the industry clustered in Silicon Valley in the first place. Surely a defining characteristic of Silicon Valley was spinoffs. Gordon Moore, the co-founder of Fairchild and Intel and author of Moore's law, argued that spinoffs were key to the clustering of the semiconductor industry in Silicon Valley (Moore & Davis 2004). It all began with Fairchild, which was distinctive both in terms of how successful it was initially and how much it was racked by internal problems that fueled spinoffs.

Exactly how spinoffs could have spurred the growth of Silicon Valley depends on how one perceives the circumstances contributing to spinoffs. If firms are limited in their ability to judge new ideas, as featured in Klepper and Thompson's (2010) model of spinoffs, then spinoffs can expand the range of promising ideas pursued in a region. Spinoffs may also have a life of their own apart from the impetus for their formation,

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[22] Consistent with this expectation, Carias and Klepper (2010) find that Portuguese entrants that located close to their parents hired a greater fraction of their initial employees from their parents. They also find that Portuguese entrants that entered the same industry as their parents were more likely to locate close to their parents, which would be expected if hiring from parents was more attractive to entrants that entered the same industry as their parents.

which can also expand the range of activities pursued in a region. Surely more needs to be understood about spinoffs to piece together their role in industry clusters. Our findings suggest that however they may have spurred the clustering of the semiconductor industry in Silicon Valley, spinoffs were instrumental in the high rate of mobility of inventors in Silicon Valley in ways that have not previously been recognized.

3 Determinants of Inventor Mobility in the Semiconductor Industry

Abstract

We identify several drivers of inventor mobility associated with two common explanations of worker turnover: matching and learning. We develop a theoretical framework to explain how incumbents, recent entrants, and spinoffs may have different motivations when hiring experienced inventors. Our hypotheses are tested on a sample of semiconductor inventors of all major merchant semiconductor producers that enter up to 1987. While most of the inventors hired by incumbents in our sample do not have prior patents, over half of the inventors hired by recent entrants and spinoffs are experienced. We find empirical support for most drivers of mobility that have been proposed in the literature in specific contexts. Drivers associated with matching seem to be more important for movements into incumbents, while drivers associated with learning seem to apply to inventors who move from parents to spinoffs. We fail to find any pattern that distinguished inventors hired by recent entrants, which leads us to conclude that further research is necessary to explain the reasons behind those hires.

3.1 Introduction

Technical knowledge has long been viewed as a critical input in the innovation process. In early research, a main concern was that if knowledge could be transmitted easily and at almost no cost between firms, there would be fewer incentives for the generation of new knowledge. This would result in an underinvestment in research and development (Arrow 1962; Nelson 1959). Since then, it has been shown that the transmission of knowledge across firm boundaries is far from easy, costless, and automatic.

Only firms that have already built up a stock of related knowledge can typically capture spillovers from the environment (Cohen & Levinthal 1990). Moreover, firms use a variety of mechanisms to prevent knowledge from leaking outside their organizations, and although none of them is perfect, they have by and large allowed firms to profit from their investment in research (Levin et al. 1987).

The acquisition, retention, and loss of knowledge are strategic problems of the firm (Winter 1987). Thus, it is important to understand the mechanisms and situations that lead to the transfer of technical knowledge. One key conduit is the mobility of technical employees. Worker mobility has received significant attention mainly from two strains of literature. One approach looks at the issue from the inventors' perspective. These works understand worker mobility as a matching process, where the inventor is looking for the firm that provides the best match for his abilities (Topel & Ward 1992; Jovanovic 1979), as this maximizes his productivity and thus his income. A different stream of research looks at worker mobility from the perspective of the firm. These works view inventor mobility as a strategy to acquire knowledge that would be difficult for the firm to develop. Some of this literature is based on the link between knowledge diffusion and enhanced inventor mobility in some regions, mostly notably in Silicon Valley (Breschi & Lissoni 2007; Almeida & Kogut 1999). Others authors have directly tested how firms' hiring of inventors away from competitors leads to learning from their hires' previous employer (Song et al. 2003; Singh & Agrawal 2011). The aim of this paper is to identify and test different drivers of mobility suggested by these two literatures, paying particular attention to how the characteristics of inventors interact with the resources and needs of firms in determining inventor mobility. More specifically, we contrast the characteristics of the inventors hired by incumbents, spinoffs and other recent entrants.

Literature on labor economics explains job mobility as a matching process between workers and employers. At the beginning of employment neither the worker nor the employer knows the quality of their match, and they learn it by observing productivity over time (Jovanovic 1979). What determines the productivity of a particular worker at a specific employer is explained in several ways. In Jovanovic's (1979) model there is a probability distribution (unknown to the worker and the employer) that determines the productivity of an employee at a given firm. Employment is the only way to discover where a given worker stands in terms of productivity at a given firm. In this context, mobility is the result of discovering a poor match. Topel and Ward (1992) use a similar argument to explain changes in employer, hypothesizing that workers change jobs to shop for better wages until they find one where their abilities are properly used and rewarded. Hoisl (2007; 2009) explores these ideas by studying the post-move productivity of mobile inventors. Her analysis is consistent with this perspective, as she finds a positive effect of mobility on productivity. In these models, moving to a firm that can make better use of the employee's abilities is what motivates changing employers. Yet, how and why some firms could generate more value using the inventor's work is typically not directly addressed. In this paper we test how the fit between the firm and the inventor affects the likelihood of the inventor's staying at his current employment or moving to a different firm. We also test how inventors help shape the technological direction of the firms they join, distinguishing their influence on incumbents, recent entrants, and spinoffs.

One of the key motivations for firms to hire inventors away from competitors is the prospect of acquiring knowledge. Since worker mobility was first identified as a likely conduit of information (Arrow 1962), several authors have demonstrated that hiring inventors is a relevant learning strategy. One group of works takes a geographical perspective and explains the diffusion of knowledge within regions through the mobility of

inventors. Their central argument is that most of the inventors who change jobs choose to remain in the same area. When they change employers, they take what they have learned with them and also act as a social connection between their old and their new organizations (Singh & Agrawal 2011). Effectively, the result of this process is that knowledge diffuses faster to co-located firms through mobile inventors (Breschi & Lissoni 2007; Almeida & Kogut 1999). Other works look more closely at the implications of hiring experienced inventors for the receiving firm. Song et al. (2003) use patent citations to the previous employers of mobile inventors and conclude that "learning-by-hiring" is a viable strategy for acquiring knowledge from other firms. They suggest that such strategy might be particularly effective when the hired inventor works in an area that is not core to the hiring firm. Subsequent works have established the usefulness of inventor mobility to acquire knowledge in fields new to the hiring firm (Singh & Agrawal 2011), to break dependencies on the hiring firm's idea generation process (Rosenkopf & Almeida 2003), to reposition the firm in the technological space (Tzabbar 2009), and as a strategy for startups to acquire knowledge (Almeida et al. 2003). Even though this literature suggests that the prospect of acquiring knowledge should incentivize hiring mobile inventors, the determinants of employee mobility are not directly addressed. If incumbents and recent entrants pursue different goals when they hire an experienced inventor, they should target workers with different characteristics. We address how the tenure and origin of the firm are related to the characteristics of the inventors it hires.

We find that spinoffs and other recent entrants are more likely to hire inventors away from other firms, while incumbents are more likely to hire inventors who have never patented before. Inventors who are productive in terms of number of recent patents filed are less likely to leave incumbent firms and join recent entrants. Inventors whose knowledge is less complementary to that of the firm are more likely to move to spinoffs or

to other recent entrants. The technological proximity between the inventor and his employer is not a good predictor of staying at the firm, but the technological proximity of the inventor with an external firm or spinoff is associated with a greater likelihood of moving to such an organization. In the case of recent spinoffs, moving inventors play an important role in determining the technical position of the firm, which suggests that the purpose of such movements is precisely to provide the technological base for these new firms. This is not the case for inventors that join recent entrants that are not spinoffs of their former employers. Finally, we find evidence that social connections through previous mobility are related to further movements between pairs of firms.

3.2 Theory and hypotheses

The aim of this paper is to explore how the tenure of the firm and its decisions regarding the acquisition and retention of knowledge shapes the mobility of inventors. We hypothesize that, because of heterogeneous needs and resources, incumbents, recent entrants, and spinoffs will pursue different strategies in terms of hiring inventors to access knowledge that lies outside of the scope of the firm. We also explore how firms' incentives to retain inventors are conditioned by inventors' knowledge characteristics, as well as its value and redundancy within the firm.

A couple of studies have directly addressed the determinants of mobility in particular contexts. Palomeras and Melero (2010) analyze the likelihood of moving away from IBM based on four characteristics of the inventors' knowledge that can affect its value to external firms: "quality, complementarity, fit within the firm's core areas, and ascription to areas in which the firm is a relevant player". Campbell et al. (2011) propose that the value of the inventor's knowledge to external firms is going to be affected by the availability of complementary assets. Employees will move as long as the contribution of

their employer's complementarity assets is not critical to value creation, or if those assets can be transferred and/or replicated in the destination firm. Ganco (2008) analyzes how the likelihood of inventors moving to different employers in the semiconductor industry changes with the complexity of their previous inventions. The novelty of the present chapter is that we cover all movements between all relevant players in an industry and analyze how the relationship between the inventors' characteristics and the potential hiring firms determines the likelihood of moving. Besides considering individual characteristics of the firm, such as its size and technical position, we examine how the firm's priorities differ across incumbents, recent entrants and spinoffs.

3.2.1 Inventor Sourcing by Entrants and Incumbents

The motivation of this paper is that recent entrants and incumbents should have different needs for hiring experienced inventors. In most cases incumbents are firms that are active at the forefront of the technology, that have a stock of relevant knowledge, and a staff of experienced workers. Their stock of knowledge enhances their "absorptive capacity", which makes it is easier for them to capture knowledge spillovers from others in the industry (Cohen & Levinthal 1990). As established firms already have most of the knowledge they use and need, and most likely possess rules and routines to train new recruits, it will be better for them to hire recent graduates and train them internally. In a survey of production engineers in the semiconductor industry, Angel (1989) finds that established firms devote significant resources to training entry-level production engineers who were hired directly out of college. These engineers subsequently move through internal and external labor markets. On the other end of the spectrum, recent entrants need to immediately staff their operations and access a variety of knowledge they do not yet possess. Thus, it will be better for them to hire experienced individuals. Lim (2009), in a case study about the diffusion of copper interconnects technology throughout the

semiconductor industry, finds that firms wanting to catch up with this technology frequently hired inventors from IBM, the firm that spearheaded the shift from aluminum interconnects. Although research on the career paths of inventors does not directly address differences between entrants and incumbents, it reveals patterns that are consistent with these ideas. For example, Moen (2005) finds that young scientists in high technology industries will accept lower salaries at incumbent firms in order to build up their human capital, and then capitalize this investment later in their careers through mobility. We propose the following hypothesis:

H1: Young firms will hire a greater portion of their employees from other firms, while incumbents will hire predominantly recent graduates.

3.2.2 Characteristics of the Inventor's Knowledge

Besides having a preference for experienced or inexperienced inventors, firms should also look at other characteristics of the inventor. Two characteristics of the inventor's work that should be related to their likelihood of moving are: quality of their patents and their dependence on co-inventors. The quality of an invention is related to its economic value and its capacity to act as a building block to generate other innovations (Hall, Jaffe & Trajtenberg 2005). The number of citations received by a patent is a proxy for the economic value of the invention (Trajtenberg 1990), and a direct measure of its utility as a building block for other patents. The likelihood of highly cited inventors switching jobs is not straightforward to determine. From one side, in the presence of outside opportunities, it may become profitable for highly cited inventors to switch jobs, as long as the value created by their innovations at the new organization compensates relocation costs (Palomeras & Melero 2010). At the same time, the current employer of highly cited inventors should be interested in retaining them, as this avoids loosing high quality

knowledge and human capital. Overall, highly cited inventors should move only when the outside opportunity is more profitable than his current employment. Palomeras and Melero (2010) show that highly cited IBM inventors are more likely to leave the firm than less-cited inventors. Campbell, Ganco, et al. (2011) find that high-income employees of legal firms are less likely to leave their employment, but when they do, they leave to form a new firm, as, in this case, it is easier for them to appropriate a greater share of their productivity.

Theory and existing evidence suggest that outside opportunities are more valuable for high-quality inventors (Palomeras & Melero 2010; Campbell et al. 2011). If outside opportunities are more valuable, it must be that the inventor's current employer is not interested in developing the latest work being advanced by the inventor, or properly compensating the inventor. These inventors could, and often attempt to, pursue the opportunity within the firm. But this is often impractical because employers have their own technology paths well chartered. Their employers do not see, or they see but do not value, the particular opportunities some high quality inventors spot and are interested in. This leaves the innovator with no other option than to form a spinoff (Klepper & Thompson 2010). In this setting, high-quality inventors who have to leave their job to follow an opportunity will most likely form a spinoff, or join a recent entrant, as this will give them greater control over their work.

H2: Compared to other inventors, highly cited inventors are more likely to stay at their current employment or leave in order to create (or join) a spinoff.

The feasibility of learning by hiring experienced inventors rests on the ability of the new hire to transfer his knowledge from the old to the new employer. If the inventor's knowledge is dependent on other inventors at the firm through co-invention, it is going to

be harder for the moving inventor to exploit his previous know-how. Thus, the dependence of an inventor on co-inventors and teamwork to generate inventions should be related to lower levels of mobility (Palomeras & Melero 2010). Ganco (2008) puts forth a similar argument, proposing that inventors whose patents depend on several underlying functions (what he deems knowledge complexity) will be less likely to move to competing firms, as it is more likely that they do not dominate all of the functions embedded in the inventions.

Considering the specific case of recent entrants, it is reasonable to assume they will face more difficulties than incumbents in learning from inventors whose knowledge is dependent on others. Due to their initial small size, it is less likely that they will have the necessary individuals to supplement the knowledge the mobile inventor does not possess. Empirical evidence confirms that recent entrants are usually narrowly focused (Almeida & Kogut 1997) and thus should not possess diverse knowledge. Moreover, the evolution of startup size is positively correlated with the likelihood of using inventor mobility as a learning mechanism (Almeida et al. 2003). In the particular case of spinoffs, the problem might be alleviated by the fact that the scope of the spinoff is close in nature to the activities of the parent (Klepper & Sleeper 2005) and as observed in Chapter 2, spinoffs hire many inventors from their parents.

H3a: The average number of co-inventors per patent an inventor has is inversely related to his likelihood of leaving his employment, and of joining a recent entrant.

H3b: The relation expressed in H3a will be less important for inventors that move from parent to spinoff.

3.2.3 Technical Proximity Between the Inventor and the Firm.

An additional factor that will certainly influence inventor mobility is the fit between firms' needs and inventors' abilities. This has been a common topic in the literature on labor economics. There is a stream of theoretical models that assume that through employment the firm and the inventor learn about their matching by observing productivity over time, and that mobility occurs when external offers that provide a better match arrive (Jovanovic 1979; Topel & Ward 1992). In the inventor mobility literature there is evidence that mobile inventors are more productive in the post-move period, which could indicate that they moved in order to improve the match with their employer (Hoisl 2009). It is also possible that an inventor with a good fit with his employer is a desirable hiring target by firms trying to emulate that employer. If the inventor's firm has a dominant position in his field of expertise, in the sense that his employer generates a great share of the innovations of such field, he will be at greater risk of getting hired away by competing firms (Palomeras & Melero 2010). Considering both effects, what ultimately determines employer mobility will be not as much the quality of the fit with his current employer but the availability of an outside opportunity that provides a better match. A way of judging the fit between a firm and an employer is by looking at their technological position. Technological positions have been characterized through characteristics of past patents, such as patent classes associated with the firm and the inventor (Jaffe 1989), or citations to those previous (Stuart & Podolny 1996).

H4a: Inventors will be less likely to stay at firms that are a poor match to their patenting activity and more likely to join firms that are a good match to it.

In the case of recent entrants and spinoffs, technological distance should greatly affect the type of inventors hired. Prior work looking at semiconductors suggests that

small entrepreneurial firms are narrowly focused, explore less crowded fields, and rely more on knowledge from their regional network (Almeida & Kogut 1997). This suggests that they should target specific types of inventors who could be helpful in advancing their main area of interest. Among these firms, spinoffs are especially noteworthy because they exploit opportunities their parent neglect (Klepper & Thompson 2010). This implies that spinoffs should hire a great share of their initial staff from the parent, particularly inventors who worked in the field of the ideas that led to the spinoff.

H4b: The technological position of the past patents of inventors hired by recent entrants, especially by spinoffs, will influence the future direction pursued by the firm.

3.2.4 Social Connections

While not directly connected to attributes of the inventor and his patenting work, social networks have important consequences for inventor mobility. The main contribution of the presence of social networks is reducing the uncertainty about the expected productivity of a prospect employee (Simon & Warner 1992). As potential employers can only get imperfect information about the marginal productivity of an inventor, the wage they offer him will include a discount proportional to the uncertainty about his productivity. The current employer has superior information on the inventor's productivity as compared to external firms and should be offering a wage that is closer to the true inventor's productivity at the firm. This asymmetric information problem imposes additional restrictions to mobility, as the gains from moving have to be large enough to overcome the discounts due to problems of asymmetric information. Social connections between a worker and his potential employers will lessen these information problems, as they provide means for the firm to get better information about the potential hire.

Empirical evidence supports the idea that social connections lead to better information about an inventor's work. Breschi and Lissoni (2007) find that inventors who are socially close are more likely to rely on the knowledge of each other, which implies they should be aware of the quality of each other's inventions. Nakajima et al. (2010) find that network-recruited inventors show longer employment duration and greater productivity during the first year than publicly hired inventors, which implies that in these cases both the firm and the inventor had more accurate expectations about the job relation. There also exists evidence on the influence of social connections on recruiting inventors. Singh and Agrawal (2011) find that, besides transferring knowledge to their new employers, moving inventors also play a significant role in recruiting additional inventors. This leads to the following hypothesis:

H5: Moving inventors are more likely to join firms to which they are socially connected through former co-workers or former co-inventors.

3.3 Sources of Data

The distinguishing feature of this paper with respect to previous works on the determinants of inventor mobility is that we evaluate our hypotheses using a data sample that includes all major semiconductor firms. We also explicitly consider how the needs of incumbents, recent entrants, and spinoffs are reflected in the type of inventors they hire. The firms included in our analysis are all firms included in the Klepper (2009) study of the origins and evolution of the semiconductor industry, which he identified from a database compiled by consulting firm "Integrated Circuit Engineering" (ICE). This database includes 101 merchant semiconductor producers that enter through 1986, and whose sales exceed certain threshold between 1974 and 1986. Klepper's (2009) data includes detailed

information on the heritage of these firms, including year of entry, their location, who the founders were, and their previous employer. We add 4 additional firms that enter in 1987.

In order to identify inventor mobility and to characterize the inventive activity of these firms' workers we rely on patent data. We focus on patents from any of 5 patent classes[23] associated with integrated circuit design and manufacturing. We download all patents granted between 1970 and 2002 from the USPTO's website. In order to isolate patents from the firms of interest, these data are complemented with the firm identifiers in the NBER patent database (Hall et al. 2001).[24] It is well known that inventors' names are inconsistently recorded in patents. In order to be able to identify all patents that belong to the same inventors we rely on the inventor identifiers from Lai, D'Amour and Fleming (2009). As this dataset contains only patents granted from 1976, we complete the missing inventors' identifiers manually. During this manual process we also merged some inventors identifiers that were discovered to be incorrectly assigned to different inventors due to false positives in the name matching algorithm.[25]

Following a growing trend in research, we infer inventor mobility from changes in assignees in consecutive patents of an inventor. For example, let us denote two consecutive patents of the same inventor as A_1 and B_2. A and B refer to the assignee of the patent,

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[23] These classes include: 257 (Active Solid State Devices), 326 (Electronic Digital Logic Circuitry), 327 (Miscellaneous Active Electrical Nonlineas Devices), 365 (Static Information Storage and Retrival), and 438 (Semiconductor Device Manufacturing).

[24] We use the 2004 update of this database, which can be obtained at: http://elsa.berkeley.edu/~bhhall/patents.html

[25] Lai et al. (2011) published an improved version of the database we used where these false negatives could have been corrected. We did not check if that was the case as we had already cleaned up our data using the older version.

and 1 and 2 refer to the year of application. If A and B are different firms, we assume that the inventor moved from firm A to firm B during year 1. If firm B is a recent entrant that entered after year 1, we consider the year of entry as the time of the movement. It is necessary to specify a few exceptions to this simple rule to cover some particular cases encountered in this process. First, if firm B acquired firm A the year before year 2, we consider that no movement occurred. Second, we encountered a few instances where inventors' had sequences of patents of the form "AAABAAA". Those cases were not classified as movements, as patent B is likely the result of inter-firm collaboration or contracting. Third, we encountered several cases where inventors had sequences of patents of the form "$A_1A_2B_3A_4B_5B_6$". In this cases we assume the inventor moved from firm A to firm B during year 2, as patent A_4 is most likely an invention that the inventor developed before year 2, but firm A only decided to patent the invention after the inventor had left. Most of the studies that use a similar method to infer mobility assume that movements happen in the mid-point between year 1 and year 2. However, after contrasting the date of the inventors' patents with the actual labor history of several inventors in our sample, which we obtained by searching in Google, we believe year 1 adjusts better to the time the movement actually happened. Finally, as we are restricting our analysis to 105 merchant IC firms of interest, when we identified a change in employers we also checked that the inventor didn't have patents at other firms in between the two patents used to identify the event. If there was an interim patent at a different firm, we excluded the move from the analysis, as the inventor moved from firm A to a firm not considered in our sample and then moved from that firm to firm B.

To construct some metrics about the impact of inventors' works, as well as the antecedents they rely upon, we use patent citations. For patents granted from 1976 we used the citations file of the NBER patent database project (Hall et al. 2001). This

contains pairwise citations between patents granted from 1976. For earlier patents we first collected as much information as possible from the USPTO's website. Then, we searched for all patents that cite patents granted to our firms of interest using the website IP.com. This website provides access to an intellectual property database constructed by combining different sources, including the USPTO and the European Patent Office. While this method retrieves as much information as possible using an automated procedure, we found a few instances where the data was incomplete due to gaps in the databases we used. These gaps do not seem to be systematic and are minor in the scope of the overall sample.

3.4 Broad Patterns and Summary Statistics

Out of 105 entrants in our database, 86 had patents. There are a total of 4880 inventors with patents or patents applications (that are eventually granted) through 1987, of which 2508 had at least two IC patents. To identify mobility events we create one observation per pair of consecutive patents. Changes of employer are inferred as explained in section 3.3. If a movement occurs, we assume the inventor moved during the year the first patent was applied for. We determined this is a good estimation of when the movement actually happened by reconstructing the actual work history of a random set of 20 inventors in our sample. To obtain the work history of these inventors we searched their names using Google, which led us to trade publications, biographies, and other sources we could use for this purpose. As our data on entry ends in 1987, we only consider observations with application date of the first patent through 1987 in order to focus on movement that happen through that year. Of 7879 observations, we identify 336 movements. In 193 cases the destination was an incumbent, in 93 cases it was a recent entrant, and in 50 cases inventors moved from parent to spinoff.

To analyze how the hypotheses outlined in section 3.2 conform to our empirical data on mobility of semiconductor inventors, we need to explore several characteristics of inventors. This section introduce the variables used for this analysis and present some summary statistics, distinguishing between inventors who do not change employers and inventors who move to different types of firms. Section 3.5 presents a formal statistical analysis of the hypotheses.

3.4.1 Hiring Patterns of Entrants and Incumbents

To evaluate hypothesis 1 we need to compare the background of inventors hired by incumbents and recent entrants. Table 3.1 contrasts the background of inventors hired by recent entrants (throughout the paper this is defined as firms 5 years old or younger) and by incumbents (throughout the paper this is defined as firms older than 5 years). Column "Hired" shows the number of inventors that patented for the first time at a firm during the time period, and column "New" shows how many of those inventors have never patented before and column "Mobile" shows how many had prior patents. These figures are reported separately for different time periods, and for firms located in and out of Silicon Valley. Figures for firms located in Silicon Valley are reported in rows identified as "SV", and figures in rows marked as "not SV" correspond to firms located out of Silicon Valley

Roughly half of the inventors hired by recent entrants, both in and out of Silicon Valley, had prior IC patents and were hired away from other ICE firms. The hiring behavior of incumbents is strikingly different, as almost all of their new hires are people

that have never patented before. This is particularly true for incumbents located out of Silicon Valley, which in general are both older and larger than Silicon Valley incumbents[26].

Table 3.1: Background of inventors hired by recent entrants and spinoffs

		Recent Entrants				Incumbents			
		Hired	New	Mobile	%Mob	Hired	New	Mobile	%Mob
Before 1971	SV	29	17	12	41%	61	57	4	7%
	Not SV	11	11	0	0%	588	583	5	1%
	Total	**40**	**28**	**12**	**30%**	**649**	**640**	**9**	**1%**
1971-1975	SV	34	14	20	59%	168	149	19	11%
	Not SV	18	13	5	28%	804	787	17	2%
	Total	**52**	**27**	**25**	**48%**	**972**	**936**	**36**	**4%**
1976-1980	SV	16	6	10	63%	237	208	29	12%
	Not SV	4	0	4	100%	814	798	16	2%
	Total	**20**	**6**	**14**	**70%**	**1051**	**1006**	**45**	**4%**
1981-1985	SV	67	22	45	67%	370	330	40	11%
	Not SV	16	5	11	69%	805	782	23	3%
	Total	**83**	**27**	**56**	**68%**	**1175**	**1112**	**63**	**5%**
After 1985	SV	46	18	28	61%	349	317	32	9%
	Not SV	20	12	8	40%	456	448	8	2%
	Total	**66**	**30**	**36**	**55%**	**805**	**765**	**40**	**5%**
Overall	SV	192	77	115	60%	1185	1061	124	10%
	Not SV	69	41	28	41%	3467	3398	69	2%
	Total	**261**	**118**	**143**	**55%**	**4652**	**4459**	**193**	**4%**

3.4.2 Characteristics of the Inventor's Knowledge

Hypothesis 2 argues that highly cited inventors would move only if they are to join a spinoff or a firm where they can have greater control over their work, which is more likely to happen at recent entrants. In table 3.2 we compare the average number of

[26] Most patents in our sample of incumbents out of Silicon Valley belong to only 3 firms: Motorola, TI, and RCA. These firms were already incumbents when Silicon Valley firms are just getting formed.

citations[27] received by recent patents[28] of inventors that join different types of firms. Movements from parent to spinoffs consider only the inventors hired by the spinoff during its first 5 years[29].

Table 3.2: Average number of citations received per patent

	Mean	Std. Dev.	Freq.	t-test*
Stayers	13.49	13.76	7543	
Movers to Incumbents	14.43	15.76	193	0.35
Movers from Parent to Spinoff	19.46	17.21	50	0.00
Movers to Recent Entrants	15.86	14.27	93	0.10

* Corresponds to the p-value of a test comparing the equality of means (two-tailed) with respect to Stayers

Inventors who do not move receive on average fewer citations per patent than inventors that move. Among movers, the only category whose mean is significantly different from the mean of "Stayers" at the 5% level is "Movers from Parent to Spinoff".

Hypothesis 2 proposed that compared to other inventors, highly cited inventors should be more likely to stay with their employer, or to move to a spinoff. In the context of this hypothesis, the number of citations received by an inventor's patents is a proxy of his work's value. Another way of measuring the quality of an inventor's work is to analyze his patenting productivity. The number of patents filed by an inventor in the last three

[27] This does not consider citations from other patents of the same assignee, as self-citations could inflate the number of citations received, portraying an incorrect account of the invention's value. We consider all citations received by the patent through the end of our sample.

[28] Recent patents are defined as all patents filed by an inventor at a given firm during the last 3 years. For the purpose of this table, we consider the patents of the inventor at the firm and time of the first patent.

[29] Note that movers to recent entrants considers movements where the receiving firm is a recent spinoff and the inventor came from a firm other than the parent.

years on behalf of his employer is directly related to his contribution to his employer's inventive activity. Table 3.3 shows the number of patents filed by the inventors in the past three years at his employer for different types of inventors.

Table 3.3: Inventors' number of recent patents

	Mean	Std. Dev.	Freq.	t-test*.
Stayers	3.91	3.91	7543	
Movers to Incumbents	2.34	2.4	193	0.00
Movers from Parent to Spinoff	2.16	1.75	50	0.00
Movers to Recent Entrants	1.91	1.43	93	0.00

* Corresponds to the p-value of a test comparing the equality of means (two-tailed) with respect to Stayers

In terms of recent patents, stayers have higher productivity than movers. The differences with each of the different categories of movers are statistically significant. The lowest patenting productivity corresponds to movers to recent entrants, albeit differences between movers are small and not statistically significant. If we think of the number of recent patents as a measure of the quality of the inventor, these patterns are inconsistent with those shown in table 3.2. While inventors who move from parent to spinoff have the highest number of citations received per patent, they have fewer recent patents than inventors who stay. However, it is not straightforward to attach an interpretation to the number of recent patents. Patenting an invention is a strategic decision, and firms may choose not to patent inventions they do not see as valuable. If this is the case, a possible explanation is that inventors that move from parent to spinoff are producing impactful innovations but in areas their employer is not interested in exploiting. It is conceivable that this is the reason why such inventors decide to leave and join (or form) a spinoff.

If the acquisition of knowledge is an important motivation for hiring experienced inventors, moving inventors must be able to transfer this knowledge effectively.

Hypotheses 3a and 3b propose that inventors whose patents have more co-inventors will be less likely to join recent entrants unless they move from parent to spinoff. If the patents of the inventor are filed with several co-inventors, the invention depends of several pieces of knowledge that are distributed among the team that created the invention. Thus, it will be harder for the mobile inventor to transfer the knowledge into new organizations. Table 3.4 shows the average number of co-inventors in the patents filed in the last 3 years by different types of inventors.

Table 3.4: Average number of co-inventors per patent

	Mean	Std. Dev.	Freq.	t-test*
Stayers	0.96	0.93	7543	
Movers to Incumbents	1	1.12	193	0.55
Movers from Parent to Spinoff	0.87	0.86	50	0.50
Movers to Recent Entrants	0.84	1.03	93	0.21

* Corresponds to the p-value of a test comparing the equality of means (two-tailed) with respect to Stayers

Inventors who do not change jobs, or that move to incumbents have on average more co-inventors per patent than inventors that move to younger firms, albeit none of these differences are statistically significant. These patterns provide little evidence in support of hypothesis 3a, and are not consistent with hypothesis 3b. Movers from parent to recent spinoffs do not seem to differ in terms of co-inventors from movers into recent entrants.

3.4.3 Technical Proximity between the Inventor and the Firm

Hypotheses 4a and 4b are based on the idea of matching between workers' abilities and firms' needs. In the case of high-tech industries a natural place to start for characterizing the match between workers and employers is to look at the technological position of each party. To characterize the technological position of firms, previous

literature has used patent citations (Stuart & Podolny 1996) and patent classes (Jaffe 1989). Measures based on patent citations rely on the degree of overlap among all citations made by the two parties being compared. In our database we observe fairly low levels of overlap; thus we start by using a coarser measure based on patent classes.

To characterize the position of the firm (or the inventor) we follow Jaffe (1989) and use the distribution of a firm's patents across the five semiconductor classes we used to identify IC patents. The vector $f_i = (f_{i1}, f_{i2}, f_{i3}, f_{i4}, f_{i5})$ describes the position of the firm (or the inventor), where f_{ik} correspond to the fraction of firm *i's* patents that contain class *k* within its classes. This definition is different from what Jaffe (1989) does in two respects: (1) we use only the five main semiconductor classes to describe the position of the firm (or inventor) instead of 49 categories aggregated from all patent classes[30], and (2) we use not only the main class of the patent, but all of the classes listed in the patent.

In order to measure the proximity between firms (or inventors) *i* and *j,* we use the angular separation between vectors f_i and f_j. This is calculated as:

$$P_{ij} = \frac{\sum_{\{k=1\}}^{5} f_{ik} f_{jk}}{\left(\sum_{\{k=1\}}^{5} f_{ik}^2\right)^{.5} \left(\sum_{\{k=1\}}^{5} f_{jk}^2\right)^{.5}}$$

This measure of proximity is analogous to what Jaffe (1998) uses and corresponds to the degree of overlap between f_i and f_j. If both vectors are identical, the measure is 1, and if there is no overlap, the measure is 0. To calculate this measure we use all IC

[30] Although the classes included in each category are not reported in Jaffe(1989), the 5 IC classes would likely fall within one or two categories as they all relate to semiconductor devices design and manufacturing.

patents granted to the firm/inventor during the last 5 years. The proximity between a firm and an inventor is denoted as *technical proximity.*

Table 3.5: Technical proximity between inventors and firms

	Source			Destination				Others			
	Mean	Std. Dev.	Freq	Mean	Std. Dev.	Freq	t-test* Source	Mean	Std. Dev.	Freq	t-test** Dest.
Stayers	0.71	0.20	7543					0.51	0.32	253734	
Movers to Incumbents	0.68	0.21	193	0.60	0.22	188	0.00	0.49	0.32	6481	0.00
Movers from Parent to Spinoff	0.72	0.19	50	0.61	0.30	20	0.05	0.52	0.31	1673	0.20
Movers to Recent Entrants	0.67	0.23	93	0.51	0.33	38	0.00	0.47	0.32	3282	0.46

* Corresponds to the p-value of a test comparing the equality of means (two-tailed) with respect to proximity with the Source firm

** Corresponds to the p-value of a test comparing the equality of means (two-tailed) with respect to proximity with the Destination firm

Table 3.5 shows the technical proximity of stayers and movers with respect to the source firm, the destination firm, and all other firms. The technical proximity between the inventors and the destination firm cannot always be computed. If the destination firm does not have recent patents, the measure is undefined. This is not a problem when the receiving firm is an incumbent, but it happens frequently when an inventor joins a recent entrant or a recent spinoff. The proximity between the inventor and other firms corresponds to the average distance between the inventor and each of the other 89 ICE firms that were active at the time of the observation and where the measure could be computed.

Hypothesis 4a proposed that inventors with a poor match with their employers are more likely to leave and that they will join firms that provide a good match. By comparing the proximity of moving inventors to the source and destination firms, we cannot conclude that inventors move to firms that are a better fit with their patent

portfolio. Moreover, the technical proximity of movers and stayers with their employers is statistically indistinguishable. The technical proximity of movers to the destination firm is lower than the technical proximity to the source firm. In all cases this difference is statistically significant. In the case of inventors that move to recent entrants, the fit with the destination firm is much lower than the fit the inventor had with his prior employer. To get a better sense on the role that technical proximity plays in the inventors' decision to join a firm, it is necessary to compare the position of the inventors with respect to firms they did not join or did not work for. The technical proximity of moving inventors to these firms is smaller than the technical proximity to the destination firm. The difference is statistically significant for the case of "Movers to Incumbents". In the case of "Movers from Parent to Spinoffs" the difference is not significant using a two-tailed test, but it would be significant at the 10% level using the single tailed version. This poor level of significance can be attributed to a small-n problem, as there are only 20 movements from parent to spinoffs where the measure could be computed. The case of "Movers to Recent Entrants" is interesting, as the difference between the technical proximity to the Destination firm and the technical proximity to Other firms is the smallest, and is far from being statistically significant. In general, the idea that inventors move to firms that provide a better fit than what they have with their current employer is not supported by the data. Nonetheless, proximity is important to some extent, as inventors do not join firms that are a bad fit. The only exception is movers to recent entrants, where proximity does not seem to be playing any role.

Hypothesis 4b suggests that the inventors hired by recent entrants and spinoffs will serve to determine the technological direction of the firm. To test this hypothesis we compute a measure similar to the technological proximity explained above. Instead of using the patents of the firm in the past 5 years, the variation introduced here uses the

patents of the firm in the next 5 years (without considering the patents of the inventor for whom the measure is being computed). We call this measure *technical convergence,* and its goal is to measure the influence of moving inventors in determining the technological trajectory adopted by the firm. Table 3.6 shows the technical convergence of inventors with the firms they join, and with other firms.

Table 3.6: Technical convergence between inventors and firms

	Destination			Others			
	Mean	Std. Dev.	Freq	Mean	Std. Dev.	Freq	t-test* Dest.
Stayers (w.r.t. employer)	0.68	0.22	7518	0.52	0.31	303654	
Movers to Incumbents	0.61	0.21	192	0.49	0.32	7564	0.00
Movers from Parent to Spinoff	0.61	0.26	32	0.51	0.30	1933	0.02
Movers to Recent Entrants	0.56	0.25	66	0.48	0.31	3781	0.04

* Corresponds to the p-value of a test comparing the equality of means (two-tailed) with respect to proximity with the Destination firm.

Comparing the technical convergence of the inventor with respect to the Destination firm and with respect to Other firms, it is clear that the future direction of the hiring firm is better aligned to the inventor's work than the future direction of other firms. These differences are statistically significant. One of the insights from table 3.5 was that inventors do not seem to move to firms that provide a better fit than their current employers. An alternative is that while the past work of the hiring firms may not be a good fit to the inventors' past work, they may be hired because the firm wants to evolve in the direction of the inventor's work. Comparing the technical distance to the destination firm in table 3.5 with the technical convergence with the destination firm in table 3.6 reveals this is not the case. An interesting observation is that the technical

convergence of movers to recent entrants with the firm that hired them is low. This contradicts the notion that these inventors were hired to shape the future position of the firm, which is partly inconsistent with hypotheses 4a and 4b. In the case of movers to incumbents and movers from parent to spinoffs, it seems that they have some influence in the direction of the firm, as at least the distance between the firm and the inventor is maintained.

A potential problem with the analysis presented above is that the measure may be too coarse. Using only patent classes to determine the position of a firm may be too broad a definition to capture differences between firms in the same industry. A more precise way of measuring technical proximity is to rely on patent citations. We use a measure based on the method of Stuart and Podolny (1996), which consists of calculating the degree of overlap in citations made by patents filed in the past few years. To compute the technical overlap between inventor i and firm j we first collect all citations made by patents filed by inventor i in the past 5 years and all citations made by patents filed in the past 5 years where the assignee is firm j. Then we calculate the fraction of patents cited by inventor i that are also cited by patents assigned to firm j. Figure 3.1 provides an illustration of this process.

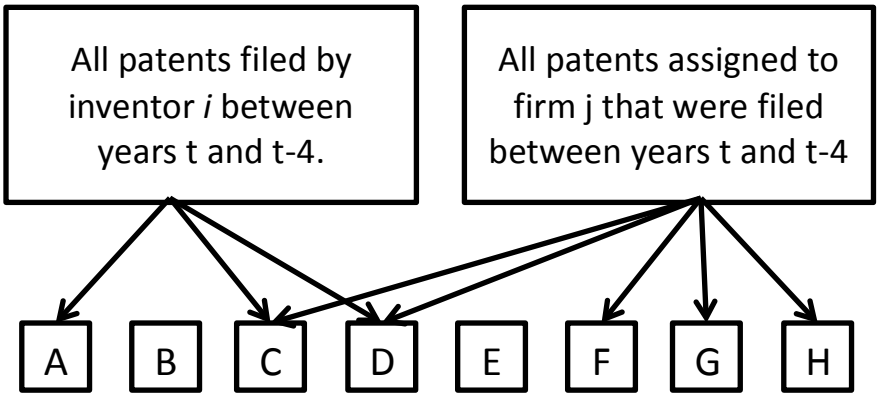

Figure 3.1: Example of technical proximity between inventor i and firm j

In figure 3.1, inventor i has cited patents A, C, and D in the past five years, while firm j has cited patents C, D, F, G, and H in the past five years. The technical overlap in this case is 0.66, and two thirds of the patents inventor i has cited in the past have also been cited by firm j. Formally, this measure of technical overlap can be computed as:

$$TO_{i,j,t} = \frac{\sum_{k=1}^{n} c_{i,k} * c_{j,k}}{\sum_{k=1}^{n} c_{i,k}}$$

Where $TO_{i,j}$ corresponds to the technical overlap between inventor i and firm j, k indexes all patents in the database, and $c_{i,k}$ is equal to 1 if firm/inventor i cites patent k between year t and year t-4.

This approach is not exempt from drawbacks. The main problem is that there is not much overlap in terms of citations between the patents filed by firms and inventors. While it is rare to observe some overlap, in the few cases when it does happen, it seems to be significant. Table 3.7 shows the technical overlap between the inventor and the destination firm, as well as to all other firms. Note the mean technical overlap reported in the table considers only cases where there was some overlap. The number of inventor/firm pairs where there was some overlap is reported in the frequency columns.

Table 3.7: Technical overlap between inventors and firms

	Destination			Others			
	Mean	Std. Dev.	Freq	Mean	Std. Dev.	Freq	t-test Dest
Movers to Incumbents	0.20	0.17	64	0.16	0.16	800	0.11
Movers from Parent to Spinoff	0.22	0.1	3	0.17	0.15	259	0.56
Movers to Recent Entrants	0.26	0.14	4	0.17	0.17	444	0.31

* Corresponds to the p-value of a test comparing the equality of means (two-tailed) with respect to proximity with the Destination firm.

From table 3.7 is not possible to draw many conclusions for the cases of movements from parents to spinoffs or to recent entrants, as there was overlap in very few cases. What is more interesting is the case of movers to incumbents. It is the case that the technical overlap is greater with the destination firm than with all other firms. However, what seems to be more important is that there are very few cases where there is any overlap between the inventor and other firms (Column frequency shows for how many inventor-firm dyad of which the measure could be calculated). Out of over 300,000 possible inventor/destinations pairs, there exists some overlap in 802 cases. In contrast, out of the 192 inventor/destinations where a movement actually materializes, there is overlap in 64 cases.

3.4.4 Social Connections

Hypothesis 5 proposes that inventors will be more likely to move to firms that former co-workers have already joined. We test this hypothesis in two ways. We first compute the number of movements that were preceded by previous movements of inventors between the same origin-destination firms (considering a 5 years window). Out of 336 movements in the sample, 85 were preceded by movements from the same origin firm. A more stringent criterion would be to consider how many movements were preceded by the movement of a former coinventor (considering a 5 years window). Out of the 336 movements, 12 were preceded by movements of former coinventors.

3.5 Statistical Analysis

3.5.1 Logit Model of Firms' Preferences Regarding Experience of Inventors Hired

Even though the tables presented in the previous section provide some evidence to support most of our hypotheses, in order to get results that control for other confounding factors, we need to use econometric techniques. Hypothesis 1 states that incumbents will be more prone to hire new graduates, while new firms prefer to hire experienced inventors. To test this hypothesis we use a series of logit models. In these models, each observation corresponds to an inventor-patent[31], and the dependent variables are dummies that identify whether the inventor is a new hire without prior patents, or a new hire that has prior IC patents at a different ICE firm[32]. The explanatory variables correspond to characteristics of the firm at the time the patent was filed. Note in these regressions we are not interested in any characteristic of the inventor; the goal is to relate the tenure of the firm with the fraction of inventors who were recently hired, either with or without experience.

The main variable of interest in these regressions is a dummy equal to one if the firm is a recent entrant. According to hypothesis 1, compared to incumbents, recent entrants will be more likely to hire experienced inventors. We also include the location of

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[31] This means that there is one observation per inventor in a patent. If a patent has n co-inventors, this will translate to n inventor-patent.

[32] If the inventor has prior non-IC patents, or patents at non-ICE firms we consider that he has no prior experience. We also tried a model where the dependent variable was a dummy equal to 1 if the inventor had prior patenting experience in non-IC fields. Those model did not provide any interesting insight.

the firm and the size of the firm as control variables. For the location of the firm we use a dummy equal to 1 if the firm is located in Silicon Valley. We expect that Silicon Valley firms are less likely to hire inexperienced inventors, because, due to the clustering of the industry in this region, the availability of trained inventors is higher there. Moreover, at the time of our study, firms located in Silicon Valley were significantly younger and smaller than the major firms outside of Silicon Valley, which according to hypothesis 1 would make them less prone to hire inexperienced inventors. To control for the size of the firm, we include the log of the number of patents filed by the firm during the year. Following the logic of hypothesis 1, larger firms should be less likely to hire experienced inventors, as they posses most of the resources and capabilities they need and can train inventors internally. The effect of firm size on hiring inexperienced inventors is ambiguous. What explains the fraction of inventors of a firm that were recently hired is growth, rather than firm size.

In model 1 the dependent variable is a dummy equal to 1 if the patent is the first patent the inventor has ever filed. In all models standard errors are clustered at the firm level. The coefficient of *Recent Entrant* is negative and significant. It implies that compared to incumbents, at recent entrants a patent is 37% less likely to include an inexperienced inventor. The coefficient of the *Silicon Valley* dummy and of *log(firm's patents)* are both negative, and only the latter is significant. Model 2 is equivalent to model 1, but it also includes firm fixed effects to capture unobservable characteristics of the firm. As the location of the firm does not change, the *Silicon Valley* dummy cannot be included in this model. The coefficient of *Recent Entrant* is slightly smaller and significant at the 5% level. Finally in model 3 we include two new variables. Chapter 2 concludes that in the semiconductor industry parents of spinoffs lose many inventors who are hired away by their spinoffs. According to the logic of hypothesis 1, incumbents should replace

these inventors by hiring inexperienced inventors, as they can train them internally. To test this idea we include the *Number of Spinoffs* variable, which counts the number of spinoffs the firm had in the past 5 years. Following the same reasoning, we can hypothesize that if inexperienced inventors are hired and trained within the firm, the first time they get a patent, it will be a co-invention, not a sole-inventor patent. We include the *Number of Co-inventors* variable to test this idea. Table 3.8 reports the coefficient estimates.

Table 3.8: Logit model of inventor's background

	Model L1	Model L2	Model L3	Model L4	Model L5	Model L6
	Inexperienced Inventors			Experienced Inventors		
Silicon Valley	-0.180			0.845***		
	(0.122)			(0.317)		
Log (Firm's patents)	-0.223***	-0.455***	-0.468***	-0.908***	-1.259***	-1.307***
	(0.069)	(0.150)	(0.139)	(0.095)	(0.106)	(0.116)
Recent Entrant	-1.005***	-0.779***	-0.658**	1.080***	0.548*	0.569*
	(0.251)	(0.291)	(0.278)	(0.229)	(0.302)	(0.314)
Number of Recent Spinoffs			0.141**			0.012
			(0.064)			(0.080)
Co-Inventors			0.080***			0.181**
			(0.015)			(0.087)
Constant	0.538*	1.503**	1.335**	-1.249***	2.057***	2.001***
	(0.324)	(0.624)	(0.575)	(0.266)	(0.346)	(0.347)
Firm Fixed Effects	NO	YES	YES	NO	YES	YES
Observations	11908	11858	11858	11908	11804	11804
Log Lik	-7886	-7753	-7729	-1038	-916.0	-911.0
Pseudo R2	0.009	0.022	0.025	0.322	0.345	0.348

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

Models 4 to 6 are analogous to models 1 to 3 but use as the dependent variable a dummy equal to 1 if the inventor is new to the firm but had prior IC patents at another ICE firm. In this case, the coefficient of *Recent Entrant* is positive and significant. The coefficient of the *Silicon Valley* dummy is also positive and significant, while the coefficient of *Log(Firm's patents)* is negative and significant. These results are consistent

with hypothesis 1. Introducing firm fixed effects reduces the magnitude and significance of the coefficient of *Recent Entrant,* but it is still positive and significant at the 10% level. The coefficient of *Number of Recent Spinoffs* is small and insignificant, which confirms the idea that parents of spinoffs replace the inventors they loose to their spinoffs by hiring inexperienced inventors, rather than by hiring experienced inventors away from other firms.

3.5.2 Conditional Logit Model of Inventor's Employment Choices

To test the remaining hypotheses, we use a conditional logit model. This model was first developed by McFadden (1973) to analyze individuals' transportation choices. Its main advantage is that it allows relating individuals' choices with characteristics of each of the different alternatives in the choice set. This type of model has been applied to a variety of settings, including location choice of new entrants (Buenstorf & Klepper 2009). In our application, after each patent, an inventor *i* may choose to file the next patent at firm *j*[33]. There are 81 ICE firms that inventors may choose to work at. Let U_{ij} be the utility that inventor *i* gets from working at the firm *(j)* of his choice. If the inventor maximizes his utility:

$$U_{ij} = Max(U_{i1}, \dots, U_{i81})$$

The utility experienced by the inventor at firm *j* depends on a vector of firm specific covariates and a random error term ϵ_{ij} with expected value equal 0 and variance equal to 1.

[33] This is equivalent to say, in between each pair of patents of an inventor, he may choose to move to firm *i*

$$U_{ij} = x_{ij} + \epsilon_{ij}$$

We assume the utility greatly depends on the inventor's salary, which will be related to the quality of his work and his fit with the firm's inventive activity. The utility experienced by the inventor is not observed, only his choice of employment is. For all pairs of consecutive patents by inventor i (which is our definition of observation), the probability that he files the second patent of pair o at firm j is:

$$p_{ijo} = \frac{\exp\{x'_{ijo}\beta\}}{\sum_j \exp\{x'_{ijo}\beta\}}$$

There are two difficulties for applying the conditional logit framework in our setting. The first is that all covariates in a conditional logit model are alternative specific (i.e., relate to the firms in our case) and our goal is to relate some characteristics of the inventor with the different choices he faces. This is easily resolved by interacting the inventor's characteristics variables with dummies that are alternative specific. A second complication is that in a conditional logit model, all alternatives in the choice set are available to the subject. In our case, not all of the 81 ICE firms are active at the time of an observation. To overcome this, we include two variables to capture when the choice is not active at the time of the observation. The variable *Dead* is a dummy equal to 1 if the firm has exited by the time of the observation, and the variable *Unborn* is a dummy equal to 1 if the firm has not been founded at the time of the observation.

To obtain a baseline of estimates, model 1 includes the control variables only. All the control variables in the baseline estimations are interacted with *Home*, which is a dummy equal to 1 if the choice firm is where the inventor is currently employed. The log of the number of patents filed by the firm during the last year, denoted *Log(firm's patents),* is included to control for the fact that mobility rates are smaller at larger firms

(Davis et al. 1998; Brown et al. 1990). *Tenure* counts the number years elapsed since the first patent of the inventor at the firm of the observation, and *Self-citations* corresponds to the percentage of the citations received by the inventor's patents that come from other patents of his employer (without considering his own patents). Both these variables are included because previous literature (Palomeras & Melero 2010) has found that inventors with longer tenure at a firm, and whose patents are mostly cited by his employer, are less likely to move out of the firm. *Recent Patents* counts the number of patents filed by the inventor in the past 3 years (from the year of application of the first patent of the pair). *Average Co-inventors* is a variable that corresponds to the average number of co-inventors per patent for patents of the inventor filed in the past 3 years. These variables are included because high levels of patenting and having many co-inventors are both associated with a smaller likelihood of leaving current employment. *Recently Acquired* is a dummy equal to one if the firm had a merger or acquisition in the past 3 years. This variable is included because inventors of firms that had been recently acquired are expected to be more likely to leave the firm if the acquisition leads to a change of priorities and strategies (Ernst & Vitt 2000). Finally, *Recent Spinoff* is a dummy equal to one if the firm is a recent spinoff of the firm of the first patent (note this variable is not interacted with *Home*). This variable is included because according to Chapter 2, spinoffs are expected to hire many inventors from their parents during their first years. All coefficient estimates in the base-line model have the expected sign, and most of them are statistically significant. Coefficient estimates are reported in tables 3.9 and 3.10.

In model 2 we start exploring how the characteristic of the choices (firms) affect the probability that inventors join them. Variables are introduced interacted with *Not Home*, which is a dummy equal to one if the firm is not the home firm. We first introduce *Log(Firm's Patents)*, whose coefficient is positive and significant. This is not surprising, as

even if a small fraction of all inventors hired by larger firms are experienced inventors, due to the vast numbers of inventors hired by them it adds up to a large figure. *Local Incumbent,* and *Local Recent Entrant* are both positive and significant, which confirms that inventors prefer to move to nearby firms. Finally, *Recent Entrant* is positive and significant, although its coefficient is the smaller of all. Note the reference group is non-local incumbents.

Table 3.9: Conditional logit models 1-3

	Model CL1		Model CL2		Model CL3	
	Coefficent	Std. Error	Coefficent	Std. Error	Coefficent	Std. Error
Home	5.092***	(0.217)	5.873***	(0.249)	4.960***	(0.329)
Home x SV	-0.529***	(0.122)	-0.048	(0.137)	0.251*	(0.143)
Home x Log(Firm's patents)	0.302***	(0.049)	0.181***	(0.052)	0.305***	(0.052)
Home x Tenure	-0.008	(0.020)	-0.017	(0.019)	-0.008	(0.020)
Home x Self Citations	0.069***	(0.011)	0.071***	(0.011)	0.066***	(0.011)
Home x Recent Patents	0.198***	(0.034)	0.210***	(0.034)	0.152***	(0.035)
Home x Avg Coinventors	0.063	(0.054)	0.070	(0.055)	0.089	(0.055)
Home x Recently Acquired	-0.529***	(0.203)	-0.639***	(0.204)	-0.475**	(0.203)
Recent Spinoffs	2.538***	(0.159)	3.819***	(0.192)	3.540***	(0.602)
Not Home x Log(Firm's Patents)			0.574***	(0.036)	0.611***	(0.037)
Not Home x Local Incumbent			0.938***	(0.128)	1.644***	(0.151)
Not Home x Local Rec Entrant			1.227***	(0.230)	1.405***	(0.237)
Not Home x Recent Entrant			0.442**	(0.190)	0.807*	(0.438)
NH x Incumbent x Rec Patents					-0.863**	(0.417)
NH x Rec Entrants x Rec Patents					-1.060**	(0.423)
NH x Rec Spinoff x Rec Patents					-0.881**	(0.429)
Home x Log(Avg Cites)					-0.004	(0.088)
NH x Incumbent x Log(Avg Cites)					-0.409*	(0.211)
NH x Rec Entrant x Log (Avg Cites)					-0.266	(0.257)
NH x Rec Spinoff x Log(Avg Cites)					-0.147	(0.298)
Dead	-2.453***	(0.595)	-1.983***	(0.667)	-1.921***	(0.667)
Unborn	-18.860	(735.056)	-17.464	(466.938)	-18.411	(757.930)
Observations	638199		638199		638199	
Log Likelihood	-2870		-2716		-2674	
Pseudo R2	0.917		0.922		0.923	

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

Models 3 and 4 introduce characteristics of the inventor's patents to assess their effect on his likelihood of joining different types of firms, which bears on hypothesis 2. In a conditional logit framework, each variable that is not alternative specific has to be interacted with alternative specific variables in order to be included. As the goal of this paper is to identify differences in hiring behavior between firms of different tenure, the inventor's characteristics are interacted with three dummies: *Incumbents, Recent Entrants,* and *Recent Spinoffs* (of the inventor's employer). The coefficient of *Recent Patents* is negative and significant for all types of firms. *Log(Avg Citations)* corresponds to the log of the mean number of citations the inventor received per patent plus one[34]. The coefficients of this variable are not significant for any type of firms, except for the case of *Incumbents,* where it is significant at the 10% level. These results suggest that the number of recent patents and the impact of those patents are not the main motivation to hire experienced inventors. This result is not consistent with hypothesis 2. Model 4 introduces the number of *Average Co-inventors* per patent. The coefficient is negative for all type of firms, but is only significant at the 10% level for *recent entrants* and *recent spinoffs*. This provides partial support to hypothesis 3, as inventors with more co-inventors, whose knowledge is conceivably harder to transfer as it is distributed among his former co-workers, are less likely to join a young firm.

[34] We add 1 to the mean number of citations received per patent to avoid the variable being undefined for inventors who have received no citations.

Table 3.10: Conditional logit models 4-7

VARIABLES	Model CL4		Model CL5		Model CL6		Model CL7	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Home	4.977***	(0.329)	4.432***	(0.388)	4.687***	(0.397)	4.465***	(0.400)
Home x SV	0.245*	(0.143)	0.245*	(0.141)	0.206	(0.143)	0.191	(0.147)
Home x Log(Firm's patents)	0.306***	(0.052)	0.306***	(0.053)	0.251***	(0.055)	0.315***	(0.057)
Home x Tenure	-0.009	(0.020)	-0.016	(0.020)	-0.023	(0.020)	-0.019	(0.020)
Home x Self Citations	0.065***	(0.011)	0.063***	(0.011)	0.061***	(0.011)	0.061***	(0.011)
Home x Recent Patents	0.151***	(0.035)	0.143***	(0.035)	0.152***	(0.036)	0.160***	(0.036)
Home x Avg Coinventors	0.005	(0.065)	-0.005	(0.065)	-0.000	(0.067)	0.035	(0.068)
Home x Recently Acquired	-0.476**	(0.204)	-0.451**	(0.205)	-0.389*	(0.208)	-0.458**	(0.210)
Recent Spinoffs	3.531***	(0.611)	3.408***	(0.608)	3.456***	(0.661)	2.960***	(0.681)
Not Home x Log(Firm's Patents)	0.611***	(0.037)	0.526***	(0.042)	0.503***	(0.043)	0.442***	(0.044)
Not Home x Local Incumbent	1.647***	(0.150)	1.633***	(0.149)	1.639***	(0.149)	1.502***	(0.153)
Not Home x Local Rec Entrant	1.393***	(0.238)	1.423***	(0.237)	1.406***	(0.240)	1.292***	(0.242)
Not Home x Recent Entrant	0.858*	(0.441)	0.727*	(0.439)	1.191***	(0.457)	1.121**	(0.456)
NH x Incumbent x Rec Patents	-0.865**	(0.412)	-0.858**	(0.416)	-1.059**	(0.449)	-1.020**	(0.446)
NH x Rec Entrants x Rec Patents	-1.062**	(0.418)	-1.050**	(0.422)	-1.241***	(0.455)	-1.181***	(0.452)
NH x Rec Spinoff x Rec Patents	-0.885**	(0.424)	-0.870**	(0.427)	-1.071**	(0.460)	-1.059**	(0.457)
Home x Log(Avg Cites)	0.022	(0.089)	0.021	(0.090)	0.036	(0.090)	0.028	(0.090)
NH x Incumbent x Log(Avg Cites)	-0.262	(0.232)	-0.267	(0.234)	-0.429*	(0.247)	-0.413*	(0.247)
NH x Rec Entrant x Log (Avg Cites)	-0.066	(0.274)	-0.027	(0.277)	-0.151	(0.286)	-0.152	(0.286)
NH x Rec Spinoff x Log(Avg Cites)	0.091	(0.321)	0.121	(0.322)	0.001	(0.332)	0.008	(0.334)
NH x Incumbent x Avg Coinventors	-0.629	(0.475)	-0.646	(0.479)	-0.723	(0.479)	-0.677	(0.477)
NH x Rec Entrants x Avg Coinvent	-0.820*	(0.488)	-0.836*	(0.492)	-0.891*	(0.491)	-0.814*	(0.490)
NH x Rec Spinoff x Avg Coinventors	-0.863*	(0.506)	-0.873*	(0.509)	-0.936*	(0.510)	-0.897*	(0.511)
Home x Technical Proximity			0.415	(0.267)	-0.263	(0.332)	-0.253	(0.333)
NH x Technical Proximity			0.240	(0.184)	-0.152	(0.210)	-0.204	(0.211)
Home x Technical Overlap			0.402**	(0.161)	0.421***	(0.163)	0.501***	(0.164)
NH x Technical Overlap			2.229***	(0.388)	2.196***	(0.392)	2.196***	(0.393)
Home x Technical Convergence					0.006	(0.345)	-0.062	(0.347)
NH x Incumbent x Tech Convergence					1.389***	(0.270)	1.414***	(0.273)
NH x Rec Entrants x Tech Convergence					0.007	(0.431)	0.011	(0.432)
NH x Rec Spinoff x Avg Tech Convergence					1.080**	(0.454)	0.943**	(0.467)
NH x Past Recent Move							0.877***	(0.134)
NH x Past Recent Coinventor Move							1.570***	(0.295)
Dead	-1.921***	(0.667)	-1.951***	(0.667)	-1.676**	(0.712)	-1.611**	(0.717)
Unborn	-18.391	(741.002)	-17.782	(535.929)	-17.781	(533.451)	-18.490	(790.359)
Observations	638199		638199		638199		638199	
Log-likelihood	-2671		-2655		-2631		-2598	
Pseudo R2	0.923		0.923		0.924		0.925	

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

Hypothesis 2 said that high-quality inventors would be more likely to join spinoffs, and hypothesis 3 said the effect of having many past co-inventors was going to be less important if the inventor was to join a spinoff. The results presented above are not

consistent with this theory. An explanation for these results is that the *Recent Spinoff* dummy is already capturing the relationship between parent and spinoffs. This implies that what seems to matter most is not the characteristics of the inventor's patents, but instead that he worked at the parent. In fact, after introducing the variables relating to the inventor's number of patents and citations received by those patents, the coefficient of *Recent Spinoffs* gets much larger.

In model 5 we add the variables measuring *Technical Proximity* (which is based on patent classes as explained in section 3.3) and *Technical Overlap* (which is based on citations overlap as explained in section 3.3). These variables are only interacted with *Home* and *Not Home* because the measures could not be computed for a sufficiently large number of recent entrants and recent spinoffs. The coefficient of *Technical Proximity* is positive for both *Home* and *Not Home*, but is not significant. The coefficient of *Technical Overlap* is positive and significant for both *Home* and *Not Home*. The coefficient corresponding to *Not Home* is significantly larger. This suggest that technical fit is more important when evaluating which firm to join rather than when evaluating whether to stay at the current employer. These results are consistent with hypothesis 4a.

Hypothesis 4b proposes that recent entrants and recent spinoffs hire inventors who can help shape the technological direction of the firm. Model 6 adds the measure of *Technical Convergence* (as explained in section 3.3), which is interacted with *Home, Not Home x Incumbent, Not Home x Recent Entrant, and Not Home x Recent Spinoff.* The coefficients of technical convergence for the interaction *Home* and *Not Home x Recent Entrant* firm are very close to zero and insignificant. The coefficients interacted with the other 2 types of potential destinations are positive. This suggests that moving inventors

are hired to influence the course of the firm[35] in the case of incumbents and recent spinoffs, but not in the case of other entrants. This is partly consistent with hypothesis 4b.

Finally, in model 7 we include variables that measure social connections. Recential Past Move is a dummy that is equal to one if inventors have moved from the firm of the first patent. *Recent Past Co-inventor Move* is equal to one if a former co-inventor has joined the firm. The coefficients of both variables are positive and significant, which supports hypothesis 5.

3.5.3 Robustness Test

As the conditional logit specification presented in section 5.2 suffers from a couple difficulties, it is necessary to test an alternative model that could provide added support for the main results presented in that section. In order to be able to include the characteristics of the inventors it was necessary to introduce these variables using two or even three way interactions. This is problematic, as the magnitude of the effect of interactions in non-linear models depend on the values of the variables in non-obvious ways, and could even have the opposite sign of the marginal effect (Ai & Norton 2003). An additional complication was that in conditional logit models, all alternatives in the choice set have to be available to the subjects. This does not happen in our setting, as at any given moment some firms have left the industry and others have not yet entered. In order to avoid these complications, we re-estimate the models using a linear probability model instead of a conditional logit. The dataset is laid out in the same way as in a

[35] It is also a possibility that those inventors were not hired to influence the direction of the firm, but because they were a good fit with the path the firm was already taking. We are not particularly interested in this distinction. What we want to evaluate is whether the past experience of the inventor is a good match to the future direction of the firm.

conditional logit, with the difference being that now choices that are not available are dropped out of the sample. This means that for each pair of consecutive patents of an inventor there will be n observations, one for each firm that is active at the time of the observation. All variables are computed in the same way as in the conditional logits. Models LPM1-LPM7 presented in tables 3.11 and 3.12 are equivalent to models CL1-CL7, but using the alternative specification.

Table 3.11: Linear probability models 1-3

	Model LPM1		Model LPM2		Model LPM3	
	Coeff.	Std. Error	Coeff.	Std. Error	Coeff.	Std. Error
Home	0.881***	(0.002)	0.881***	(0.002)	0.886***	(0.003)
Home x SV	-0.053***	(0.001)	-0.053***	(0.001)	-0.052***	(0.001)
Home x Log(Firm's patents)	0.014***	(0.001)	0.014***	(0.001)	0.014***	(0.001)
Home x Tenure	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
Home x Self Citations	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
Home x Recent Patents	-0.001	(0.001)	-0.001	(0.001)	-0.000	(0.001)
Home x Avg Coinventors	0.004***	(0.000)	0.004***	(0.000)	0.004***	(0.000)
Home x Recently Acquired	-0.070***	(0.003)	-0.070***	(0.003)	-0.070***	(0.003)
Recent Spinoffs	0.017***	(0.001)	0.018***	(0.001)	0.010***	(0.003)
Not Home x Log(Firm's Patents)			0.001***	(0.000)	0.001***	(0.000)
Not Home x Local Incumbent			0.002***	(0.000)	0.002***	(0.000)
Not Home x Local Rec Entrant			0.002***	(0.000)	0.002***	(0.000)
Not Home x Recent Entrant			0.000***	(0.000)	-0.000	(0.001)
NH x Incumbent x Rec Patents					-0.000***	(0.000)
NH x Rec Entrants x Rec Patents					-0.000**	(0.000)
NH x Rec Spinoff x Rec Patents					-0.002***	(0.000)
Home x Log(Avg Cites)					-0.003***	(0.001)
NH x Incumbent x Log(Avg Cites)					-0.000***	(0.000)
NH x Rec Entrant x Log (Avg Cites)					-0.000	(0.000)
NH x Rec Spinoff x Log(Avg Cites)					0.005***	(0.001)
Constant	0.001***	(0.000)	-0.000**	(0.000)	0.001***	(0.000)
Observations	400033		400033		400033	
R-Squared	0.902		0.902		0.902	

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

The results of the alternative specification are for the most part consistent with the results presented in section 5.2. There are a few differences that are worth mentioning. In LPM3, the coefficient of *Not Home * Rec. Spinoff * log(Avg. Citations)* is now positive and significant. This difference makes the results more in line with hypothesis 2. In LPM4, the coefficient of *Home * Tech. Distance* is now positive and significant, but the coefficient of *Home * Tech. Overlap* is no longer significant. This is does not change the main argument presented in section 5.2. It suggests that to remain employed at a firm it is important that the inventor works in areas that are well aligned with the employer. Instead, for moving into a firm it seems more important that there is some overlap in the antecedents used by the inventor and the potential employer. In LPM5, when the variable *Home * Tech. Convergence* is introduced, the coefficient of *Home * Tech. Distance* turns negative and significant. That effect is picked up by the coefficient of *Home * Tech. Convergence,* which is now positive and significant. This is quite reasonable, as it implies that in terms of fit between the inventor and the firm, the most important consideration for staying at the same employer is that the work of the inventor is well aligned with the future direction of the firm.

An added benefit of the linear probability model is that the coefficients can be readily interpreted as the marginal effect. Looking at the magnitude of the coefficients it seems that the characteristics of the inventor's past patents have very little influence in the type of firms they join. The only relevant pattern is that highly cited inventors are more likely to join spinoffs. The firms that seem to have the greatest attraction are recent spinoffs of the inventor's employer, firms to which the inventor has some level of technical overlap, and firms where former co-inventors have already moved. As it is natural, the most likely decision is that the inventor will remain in the same firm, a decision that is

reinforced if the work of the inventor is well aligned with the firm, or if the employer is a major firm.

Table 3.12: Linear probability models 4-7

	Model LPM4		Model LPM5		Model LPM6		Model LPM7	
	Coefficent	Std. Error	Coefficent	Std. Error	Coefficent	Std. Error	Coefficent	Std. Error
Home	0.886***	(0.003)	0.857***	(0.004)	0.861***	(0.004)	0.861***	(0.004)
Home x SV	-0.052***	(0.001)	-0.051***	(0.001)	-0.052***	(0.001)	-0.052***	(0.001)
Home x Log(Firm's patents)	0.014***	(0.001)	0.016***	(0.001)	0.013***	(0.001)	0.013***	(0.001)
Home x Tenure	-0.000***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)	-0.001***	(0.000)
Home x Self Citations	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
Home x Recent Patents	-0.000	(0.001)	-0.001	(0.001)	-0.001*	(0.001)	-0.001	(0.001)
Home x Avg Coinventors	0.004***	(0.000)	0.004***	(0.000)	0.004***	(0.000)	0.004***	(0.000)
Home x Recently Acquired	-0.070***	(0.003)	-0.068***	(0.003)	-0.063***	(0.003)	-0.063***	(0.003)
Recent Spinoffs	0.010***	(0.003)	0.010***	(0.003)	0.003	(0.003)	0.003	(0.003)
Not Home x Log(Firm's Patents)	0.001***	(0.000)	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Not Home x Local Incumbent	0.002***	(0.000)	0.002***	(0.000)	0.002***	(0.000)	0.002***	(0.000)
Not Home x Local Rec Entrant	0.002***	(0.000)	0.002***	(0.000)	0.002***	(0.000)	0.001***	(0.000)
Not Home x Recent Entrant	-0.000	(0.001)	-0.000	(0.001)	-0.001	(0.001)	-0.001	(0.001)
NH x Incumbent x Rec Patents	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
NH x Rec Entrants x Rec Patents	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
NH x Rec Spinoff x Rec Patents	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)
Home x Log(Avg Cites)	-0.003***	(0.001)	-0.004***	(0.001)	-0.005***	(0.001)	-0.005***	(0.001)
NH x Incumbent x Log(Avg Cites)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)	-0.000***	(0.000)
NH x Rec Entrant x Log (Avg Cites)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
NH x Rec Spinoff x Log(Avg Cites)	0.006***	(0.001)	0.006***	(0.001)	0.006***	(0.001)	0.006***	(0.001)
NH x Incumbent x Avg Coinventors	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)
NH x Rec Entrants x Avg Coinvent	-0.000*	(0.000)	-0.000*	(0.000)	-0.000*	(0.000)	-0.000*	(0.000)
NH x Rec Spinoff x Avg Coinventors	-0.004***	(0.001)	-0.004***	(0.001)	-0.004***	(0.001)	-0.004***	(0.001)
Home x Technical Proximity			0.039***	(0.003)	-0.035***	(0.004)	-0.035***	(0.004)
NH x Technical Proximity			-0.000	(0.000)	-0.000	(0.000)	-0.000	(0.000)
Home x Technical Overlap			-0.001	(0.002)	0.002	(0.002)	0.002	(0.002)
NH x Technical Overlap			0.014***	(0.002)	0.014***	(0.002)	0.014***	(0.002)
Home x Technical Convergence					0.089***	(0.003)	0.089***	(0.003)
NH x Incumbent x Tech Convergence					0.000	(0.000)	0.000	(0.000)
NH x Rec Entrants x Tech Convergence					0.000	(0.000)	0.000	(0.000)
NH x Rec Spinoff x Avg Tech Convergence					0.019***	(0.002)	0.019***	(0.002)
NH x Past Recent Move							0.001***	(0.000)
NH x Past Recent Coinventor Move							0.017***	(0.002)
Constant	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
Observations	400033		400033		400033		400033	
R-Squared	0.902		0.902		0.902		0.902	

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

3.6 Conclusions

The literature on inventor mobility has highlighted the role of moving workers in transferring knowledge from their previous organizations. Most of these works are based on observing the behavior of the receiving firm after an inventor moves. Instead, we examine the conditions that lead to hiring experienced inventors and the profile of the inventors hired. As Chapter 2 established, recent spinoffs hire many inventors away from their parents; we therefore focus on the differences between incumbents, recent entrants, and spinoffs. Following the literatures on labor markets and on knowledge spillovers, we identify and test several drivers of mobility in a sample of semiconductor inventors. Our results show that over half of the inventors hired by recent entrants and spinoffs have prior patents, while only a small fraction of all inventors hired by incumbents have prior patenting experience. Very few characteristics of the inventors' past patents seem to have an important effect on worker mobility. Inventors who move have less recent patents, and only inventors who move from parent to spinoffs stand out in terms of citations received by their past patents. The factors that seem to be more important for determining mobility are spinoffs' heritage, technical overlap between firms and inventors, and social connections through former co-workers. As we discuss below, these results vary from the prevailing view that knowledge acquisition is a primary driver of mobility.

Based on the findings of the literature on "learning by hiring", our hypotheses maintained that highly cited and highly productive inventors should be more likely to move. The preferred destination would be firms where they have greater control over their work, namely recent entrants and recent spinoffs. We have little evidence to support this view. If anything, it seems that highly productive inventors are less likely to move. We did find some evidence that inventors who move from parent to spinoffs are more highly cited

than others, but these results were only significant in some of our analyses. This leads us to believe that learning is not necessarily the main motivation behind many of the mobility events. However, it is necessary to exercise some caution when interpreting this result. Using patent data entails many difficulties. In this case, a main concern is that patents are an imperfect proxy of the inventor's work. It may well be the case that inventors who move out of the firm have fewer patents because their employer decided not to file patents for their work. If the worker's employer was not interested into further developing the inventor's line of work, it is reasonable that the firm did not file for patents on that work, and that the inventor left for another firm where he could develop his interests.

The factors that seemed to have the greater influence were based on the matching between the firm and the inventor. Inventors whose patents are aligned with the overall technological position of the firm were less likely to move. Similarly, external firms were more likely to hire inventors with whom they had some technical overlap. While the effect of technical overlap seems strong, it is important to point out that there are few instances where firms and inventors overlap. A high level of overlap happens when many of the patents cited by the inventor have also been cited by other patents of the firm. While this is an infrequent event, when it does happen, it seems to be important for determining inventor mobility. We also explored how moving inventors will influence the overall direction of the firm. Following the "learning by hiring" logic, we would expect that inventors hired from competitors have a great influence on the direction taken by the hiring firm. The strongest link was in the case of inventors who moved from parent to spinoffs. There was no evidence that inventors hired by recent entrants from firms other than the parent had an influence in the direction of the firm.

In what we believe is the first attempt to test drivers of inventor mobility using a sample that includes most of the firms in an industry, we find only partial support for the two main reasons given in the literature to explain mobility. If learning is the main motivation, it is puzzling that in the only case where a inventor's past work stands out is in movements from parents to spinoffs. That moving inventors have little influence in affecting the technical direction of the firm is also inconsistent with the learning explanation. Only inventors hired by recent spinoffs from their parent seem to have a significant effect on determining the path of the firm. If finding a better match is the main reason inventors move to new employers, it is hard to explain that the fit of the inventor with the receiving firm is no better than the fit with his previous employer. Using a detailed measure of technical overlap based on co-citations between firms and employers, we find that having some overlap is an important determinant of mobility. However, only in about 20% of the movements (71 out of 336) in our sample does the inventor have some overlap with the destination firm, and most of this cases correspond to inventors moving between incumbents (64 of the 71).

The results presented in this paper indicate that there is not one single explanation for inventor mobility. Inventors whose patents seem to be more significant are more likely to join spinoffs and have a greater influence on the direction of the firm, but this does not apply to inventors who move to incumbents or to recent entrants. Technical overlap appears to have a strong influence on mobility, but overlap is a rare event and most of the movements where there is technical overlap correspond to inventors moving between incumbents. Overall, in only about a third of the movements where the destination firm is an incumbent, was there some technical overlap. Finally, there is not a clear driver associated with movements to recent entrants. This type of movement represents about a third of all movements in the sample, and we didn't identify any particular characteristic

of inventors who join recent entrants. These patterns make necessary further study to determine what firms do with the previous knowledge of inventors. Our results provide limited support for the drivers of mobility previously identified, but there are still many movements that do not seem to have a clear explanation.

4 How Recent Entrants in the Semiconductor Industry Learn from their First Employees

Abstract

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 suggest that unless the inventor is hired from the spinoff's parent, he will not bring in much knowledge from his previous employer. Instead, by hiring experienced inventors firms acquire a stock of knowledge that enhances their ability to capture spillovers and improve their knowledge brokering capability. While we observe a strong technical link between parents and spinoffs, this seems to be independent of the number of inventors hired from the parent. While most spinoffs hire many inventors away from their parents, even spinoffs that hire relatively few of them also exhibit a strong technical liaison with their parents.

4.1 Introduction

Long ago, Arrow (1962) noted that the mobility of employees among firms could be a conduit for the transfer of knowledge. Many years passed until this assertion was empirically tested, mainly due to the difficulty of observing information flows. Since Jaffe, Trajtenberg, and Henderson (1993) used patent citations to measure knowledge spillovers in their seminal article on the geographical localization of knowledge, a large literature on information flows has ensued. Several works have covered different aspects of the relationship between worker mobility and knowledge diffusion. Empirical evidence suggests that movements of inventors between firms are followed by flows of information (Song et al. 2003; Singh & Agrawal 2011).

The learning effect of inventor mobility has important geographical implications. When inventors change employers they tend to stay in the same area, which results in knowledge diffusing mostly to nearby locations (Breschi & Lissoni 2006). Moreover, some regions exhibit intensified labor mobility, propelling the area's diffusion of knowledge. The semiconductor industry is an iconic example of agglomeration and heightened inventor mobility. The industry is highly concentrated in Silicon Valley, a region characterized by a fluid labor market (Saxenian 1994) and rapid knowledge diffusion.

Silicon Valley is also famous for the role spinoffs had in the growth of the semiconductor industry (Klepper 2010). The continued creation of new firms in Silicon Valley had significant consequences for inventor mobility rates. As explained in Chapter 2, most of the increased inventor mobility in this region is connected to workers moving from incumbents to new firms. The reasons behind this hiring pattern cannot be understood from the existing literature. Most of the learning-by-hiring literature has centered on the exchange of inventors between established firms. Thus, it is ill suited to explain how recent entrants leverage the experience of their initial hires. A better understanding of how startups benefit from hiring experienced workers is necessary to determine how, and to what extent, the greater availability of workers in agglomerated regions facilitates firm entry. This could also shed some light into determining to what extent the agglomeration of firms in Silicon Valley, rather than the spinoff process, was responsible for the extraordinary growth of this region.

This paper looks at how firms benefit from the previous experience of the inventors they hire during their foundational phase. We argue that acquiring 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 et al. 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 & Levinthal 1990). Young entrants may overcome their initial lack of experience and knowledge accumulation by hiring experienced workers. We propose that most of the inventors hired by new firms will help build those firms' capabilities, and only few will provide specific knowledge necessary for the firm's initial undertakings.

Generally, it is difficult to determine which inventors are hired for building up a firm's capabilities and which are hired to acquire specific pieces of knowledge. However, the heritage of spinoffs provides an opportunity to observe this. The initial undertakings of spinoffs are related to the activities of their parents, and they usually stay in the same geographical area to leverage their pre-entry industry knowledge (Buenstorf & Klepper 2009; Figueiredo et al. 2002). One of the reasons spinoffs locate close to their parents is to hire inventors away from them. Conceivably these inventors are hired because they are knowledgeable in the area the spinoff expects to pursue. Spinoffs will not be able to hire all necessary inventors from their parent and, therefore, hire additional workers from other sources. This group of inventors will have disciplinary knowledge that is useful to the spinoff, but will not necessarily be expert on the specific work the spinoff is developing.

Following a large literature on knowledge diffusion, we 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, the knowledge embedded in the inventor gets transferred to the new organization. The part of this knowledge that the inventor acquires by solving

particular problems at his previous employer (March & Olsen 1975; Levitt & March 1988) is what we deem as firm specific knowledge. 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 acquired vicariously (Levitt & March 1988; Argote, McEvily & Reagans 2003). We denote this knowledge as industry wide knowledge, as it corresponds to knowledge that has thoroughly diffused across different firms in the industry. 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 wide 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 wide 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 wide 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; thus inventors are not hired as a consequence of an increase in use of the knowledge of their employers. 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.

The rest of the paper is organized as follows. In section 2, we present a brief reprise of the importance of inventor mobility on the early years of the semiconductor industry.

Section 3 develops a theoretical framework on how incumbents, recent entrants, and spinoffs use the previous knowledge of the inventors they hire. Section 4 describes the different sources of data used to test our hypothesis. Section 5 presents some broad patterns of hiring at different firms along with its implications for learning, and statistically tests our theory. In section 6, we provide some discussion of our findings and conclusions.

4.2 Inventor Mobility in the Semiconductor Industry

The semiconductor industry originated with the invention of the transistor at Bell Labs in 1947 by John Bardeen, Walter Brattain, and William Shockley. Before the invention of the transistor, there already existed an electronics industry that was formed by firms such as RCA, Sylvania, Raytheon, GE, and Westinghouse. These firms were concentrated in New York, Boston, and Los Angeles (Klepper 2009).

An interesting fact about the semiconductor industry is that firms new to the field introduced almost all of the innovations that led to the invention of the integrated circuit, which is the now omnipresent device that spurred the outstanding growth of the industry. While established electronics producers had significant resources and an established workforce devoted to vacuum tubes[36], the new firms had to build their staffs from scratch. A common factor of successful new firms is that they built their research staffs around people who had worked on the invention of the transistor at Bell Labs. We present a brief recount of how the most influential firms in the early development of the integrated circuit established their semiconductor operations.

[36] Vacuum tubes are the devices that the transistor eventually replaced.

The first semiconductor firm established in Silicon Valley was Shockley Semiconductor Laboratory. William Shockley, who had co-invented the transistors at Bell Labs in 1947, founded the firm in 1956 with the goal of bringing the silicon diffused mesa transistor developed at Bell Labs to the market. Even though Shockley had managed to recruit an extremely talented team, the firm never succeeded in getting any product to the market. In 1957, after Shockley had abandoned his plans to develop silicon transistors, eight of his initial employees left to form Fairchild Semiconductors. Unlike Shockley Semiconductor, Fairchild was a very successful firm whose employees brought major innovations to the industry. Gordon Moore and David Allison created the first commercial silicon diffused mesa transistor, Jean Hoerni introduced the planar process, and later Robert Noyce devised how the planar process could be used to produce integrated circuits. While these were major innovations, at the time there was no consensus within Fairchild on how to seize these opportunities. This situation, along with other internal tensions led many employees to leave Fairchild and form their own spinoffs (Lécuyer & Brock 2010)

Another important firm in the development of the industry was Texas Instruments (TI). By the time the transistor was invented at Bell Labs, TI had recently diversified from geophysical services to the production of defense electronics. To create its central research lab the firm hired Gordon Teal, who had previously worked at Bell Labs developing transistors by growing single crystals of germanium or silicon. The team led by Teal introduced the first silicon transistor[37], which allowed TI to dominate the early market of silicon transistors (Lécuyer & Brock 2010). Later on, the firm was first in demonstrating a working integrated circuit.

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[37] This was a junction type transistor, a less advanced device than the mesa transistor or the planar transistor introduced later by Fairchild.

Most electronic producers that diversified into semiconductors were never very successful. They did dominate the industry during the first few years by producing mostly germanium junction type transistors, but as innovations were introduced into the market, they could not keep up with the new developments. When Fairchild announced the first planar transistor in March 1960, the industry was quickly interested in the process, which was seen as a major innovation. Texas Instruments and Motorola acquired the competency fairly quickly, while Philco and Transitron, two electronic diversifiers that had strong germanium product lines, were slow into developing it (Lécuyer & Brock 2010). Motorola, an electronics firm that had been around for several years before the transistor was invented, did something unusual among incumbents when establishing its semiconductor capabilities. While Motorola was based in Chicago, IL, its leaders decided to put Motorola's semiconductor operations in Scottsdale, AZ, hiring mostly new staff. To head the division they hired Lester Hogan, who at the time was at Harvard University and had previously worked at Bell Labs under William Shockley (Holbrook et al. 2000).

The historical evidence presented above suggests that, in the early years of the semiconductor industry, the firms that were successful in keeping up with the developments that led to the invention of the integrated circuit were those successful in internalizing knowledge that was generated elsewhere. An important source for this knowledge was Bell Labs, and all firms presented above hired key employees from Bell. This supports the idea that the mobility of inventors was a key factor in the diffusion of knowledge, and that new firms were active in recruiting inventors.

If we look at regional level data, the evidence shows that inventor mobility benefited some regions more than others. Initially the industry was concentrated in New York, Boston, and Los Angeles, where the large electronic producers were located. These

regions lost importance to the emerging Silicon Valley cluster, which was characterized by an unusually high rate of inventor mobility (Saxenian 1994). Yet, this heightened mobility seems to be caused mostly by recent entrants. A survey of semiconductor engineers conducted by Angel (1989) shows that new firms tend disproportionately to hire experienced engineers, while incumbents mostly hire entry-level engineers right out of college through on-campus recruitment. To aid our understanding of the patterns explained above, we will next provide a theoretical framework on how recent entrants and incumbents leverage the previous knowledge of the inventors they hire.

4.3 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 et al. 2003; Singh & Agrawal 2011; Rosenkopf & 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 & 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 et al. 2003; Rosenkopf & Almeida 2003), even in cases where the prior firm has exited the market (Hoetker & 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 & 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. In a more recent reconceptualization, 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 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 vicariously 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 disciplinary and specific knowledge.

4.3.1 Incumbents

The literature has mostly focused on the acquisition of firm specific knowledge from inventors' previous employers. Studies using varied methodologies consistently find that when an inventor changes employers, knowledge gets transferred from the source to the destination firm (Singh & Agrawal 2011; Song et al. 2003; Rosenkopf & 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 et al. 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 our 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 acquire disciplinary absorptive capacity should be limited. While hiring experienced inventors will also result in the acquisition of industry wide knowledge, this is not the

main objective for incumbents. The disciplinary knowledge inventors bring is more likely to be redundant when the hiring firm is an incumbent.

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

4.3.2 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 & 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 wide 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 disciplinary training 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 wide knowledge.

4.3.3 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 our study, were spinoffs and eventually these were also nearly all of the industry leaders (Klepper 2010)[38].

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 & 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 & Sleeper 2005) or whose value was misjudged by it (Klepper & Thompson 2010). In the semiconductor industry, disagreements about the value of inventions and on the course the firm should follow were prevalent (Klepper

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

& Thompson 2010). This resulted in many influential inventions being made at incumbents and developed at spinoffs. As explained in Chapter 2, during their first years spinoffs draw many inventors from their parents to staff their initial endeavors with workers knowledgeable about the idea that led to the spinoff. 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.

Contrasting with the hiring of new firms from unrelated incumbents, the hiring of inventors from the parent firm is deliberate and focused. Therefore, we do not expect this hiring to have an effect on the absorptive capacity of the spinoff firm.

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

Table 4.1 summarizes the hypothesis in terms of firm specific and industry wide knowledge acquisition. For producing this table, the amount of knowledge transferred is classified as low/medium/high in a way consistent with the relationships established in the hypotheses.

Table 4.1: Summary of hypotheses.

Type of Movement	Firm Specific Knowledge	Industry Wide Knowledge
H1: Incumbent to incumbent	Medium	Low
H2: Incumbent to recent entrant	Low	High
H3: Incumbent (parent) to spinoff	High	Low

4.4 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 the 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[39] 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

[39] All firms whose annual sales exceed a certain threshold are included in the compilation.

were[40] 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[41] 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 database (Hall et al. 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.

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.

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[40] Founder is defined as someone who organizes the firm and initially works at it.

[41] 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).

Extending this manual verification to patents granted beyond 1976, we also adjusted the classification for a small number of inventors[42].

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[43]. 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[44], and excluded all movements where we found a third employer.

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[42] 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 cleaned up our database manually; thus we had little to gain by updating to the new dataset.

[43] 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.

[44] 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. Based on the post 1976 figures this is not a concern.

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 firm or adopts a managerial role at the new organization. The date we assign to the inventor movement has important consequences for our 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.

Our 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. This indicates that even among our sample of large firms, many firms did not have any patents. Thus, including lesser firms would not contribute much to the analysis. The earliest application year is 1961, but patents applied before 1967 are scarce. The time covered by our database allows us to have a sizable number of patents when major players of the industry were entering in Silicon Valley. When identifying movements we restricted our attention to 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 is only available in electronic form for patents granted from 1976. The NBER patent database project (Hall et al. 2001) compiled a database of pairwise citations with the information available from the USPTO. We use this dataset for patents applied from 1976[45]. 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 information from the

[45] 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.

DOCDB[46] 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 et al. 2001) to identify the assignees of the citing patents.

4.5 Statistical Analysis

4.5.1 Hiring Patterns

Before analyzing how hiring firms use the mobile inventors' previous knowledge, we report some figures regarding hiring choices by different types of firms. 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 4.2 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[47] 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

[46] 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

[47] This choice is an arbitrary threshold. We experiment using a larger threshold and found that enlarging the period where firms are considered recent entrants does not add many movements from other firms.

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 4.2: Origin of inventors hired by recent entrants and incumbents

	Recent entrants (5 yrs or younger)				Incumbents (Older than 5 yrs)			
	Hired	New	Mobile	% Mod	Hired	New	Mobile	% Mob
1971 to 1975	52	27	25	48%	972	936	36	4%
1976 to 1980	20	6	14	70%	1051	1006	45	4%
1981 to 1985	83	27	56	67%	1175	1112	63	5%
After 1985	66	30	36	55%	805	765	40	5%
Total	221	90	131	59%	4003	3819	184	5%

Table 4.2 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 entrants disproportionately need experienced inventors to get the firm started. We now turn to analyzing how incumbents and recent entrants leverage the experience of the group of inventors hired from other firms.

4.5.2 Tracing Knowledge Flows

We follow an extensive tradition of works that use patent citations as a proxy for knowledge flows[48]. 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

[48] 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.

firm to previous patents of the moving inventor with citations made to a similar patent of a different firm. A major drawback of this methodology is that it ignores potential unobservable difference 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 (Singh & Agrawal 2011). Even with careful selection of the control group, the moving inventor's patents can be more valuable to the hiring firm. If this were 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 situation. Their identification strategy is based on differences in citation rates between the pre-move and the post-move period. But when dealing with 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 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 & Almeida 2003; Oettl & Agrawal 2008; Almeida et al. 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 4.1 explains the novelty of our analysis in analyzing the flow of knowledge between a citing and a cited firm. Previous

studies have centered on how the hiring of inventors by the citing firm can lead to an increase in citations from the citing to the cited firm[49]. This is what we call the acquisition of *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. This is what we define as the acquisition of *industry-wide* knowledge. The citing firm is acquiring expertise in inventions developed by the citing firm indirectly by hiring inventors from other firms. Conceivably, as industry wide knowledge has diffused throughout the industry, these inventors acquired this knowledge vicariously through past employment.

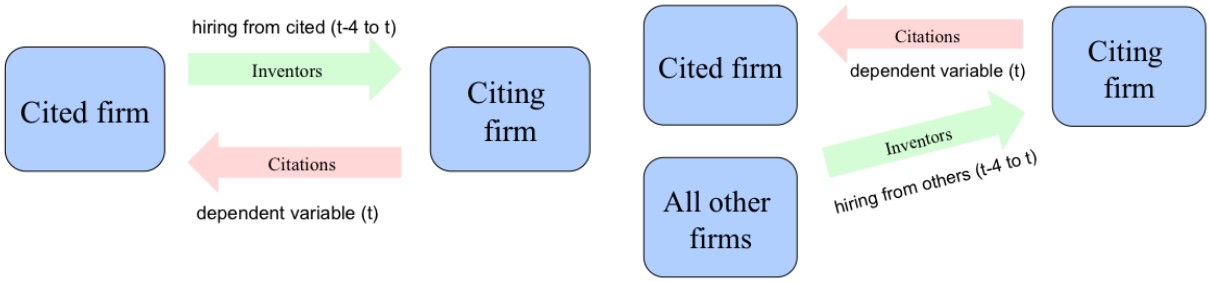

Figure 4.1: Measuring acquisition of firm specific knowledge (left side) and of industry wide knowledge (right side).

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

[49] Not all previous works analyze knowledge flows between dyads of firms. Oettl and Agrawal (2008) analyze knowledge flows between source firm and destination country.

exited the market are dropped. Calling one of the firms in the dyad "citing firm" and the other "cited firm", the dependent variable $Citations_t$ 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. The variables are explained in detail as we introduce the models, and Appendix B provides a summary table and some descriptive statistics.

We 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 & 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 & 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.

Table 4.3: Coefficient estimates for negative binomial models of citations between dyads of firms.

	Model 1	Model 2	Model 3	Model 4
Hired from cited	0.279***	0.223***	0.366***	0.367***
	(0.076)	(0.052)	(0.081)	(0.082)
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)
Hired from cited * leader			-0.175	-0.179
			(0.121)	(0.123)
Hired from leaders – hired from cited * leader			0.082**	0.080**
			(0.040)	(0.040)
Recent spinoff (10 years)				0.724*
				(0.371)
Constant	-9.041***	-9.190***	-9.212***	-9.223***
	(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 the first model, we introduce the two hiring count variables, along with all controls. Coefficient estimates are presented in Table 4.3. The "*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 "*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[50]. 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 effect of the *hired from others* variable is much smaller than the effect of the *hired from cited* variable, bear in mind that *hired from others* aggregates hiring from several firms. The coefficients of the control variables largely 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 of the local diffusion of knowledge[51] 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 wide knowledge. In subsequent models we introduce a series of variations to understand better who benefits the most from each type of learning.

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

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[50] This means that a 1 unit change in the independent variable is associated with a percent change equivalent to exp(B)-1.

[51] 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.

only considering the hiring that occurs while the citing firm is a recent entrant (5 years old or younger). *"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[52]. 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 *hiring 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%[53]. 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 *Hiring 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

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[52] 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.

[53] This considers the coefficients *Hired from cited* and *Hired from cited * spinoff.*

hiring firm is a recent entrant and the inventors were not hired from the parent[54]. 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%[55]. These results largely conform to hypotheses 3a and 3b, which postulate that inventors hired by recent entrants contribute mostly by bringing industry wide knowledge rather than specific knowledge from their previous employer.

After introducing the initial hiring count variables, the coefficients of the *Hiring from cited,* and of the *Hiring from others* variables slightly dropped, but both are still significant. According to hypothesis 1b, the coefficient of *Hiring from others* should not be significant, as we did not expect the acquisition of industry wide knowledge to 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 established firms there will technological leaders and laggards. These will differ in terms of their needs for external knowledge, as well as in the value of its knowledge for external firms. A leader 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 patents: Texas Instruments, Motorola, and RCA.

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[54] 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.

[55] This corresponds to the coefficients *Hired from other* and *Hired from other * (1-spinoff).*

We introduce two additional variables to measure the industry wide 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 *"Hiring from leaders".* By including the variable "*Hiring from leaders - Hired from cited * leader"*, this variable is used to measure the acquisition of industry wide knowledge that results from hiring inventors from the leaders. In the cases where the cited firm is one of the leaders, the numbers of inventors hired from them is subtracted to prevent the coefficient from including the acquisition of specific knowledge from the cited firm. 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 wide 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 our 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 neighboring firms. The evidence we find conforms to this theory, but the residual effect captured by the *Local SV* and *Local not SV* suggests there are also other knowledge diffusion mechanisms in place[56]. 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 additional to inventor mobility. To test this, in model 4 we include the *"Recent spinoff (10 yrs)"* dummy[57]. This is equal to one if the citing firm is a spinoff of the cited firm and 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 *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.

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[56] Estimating the models without any of the hiring variables yields bigger coefficients for *Local SV* and *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 *Local SV* drops more than the *local not SV* coefficient, implying that knowledge diffusion through inventor mobility is more important in Silicon Valley than in other areas.

[57] 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.

4.5.3 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 4.4, 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. 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[58].

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[58] 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

Model 6 is equivalent to Model 4 including the *"hiring of inexperienced inventors"* variable. The coefficients estimated 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 4.4. 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 – hiring from cited * leader* is significant when measuring future hiring. While this question of whether hiring mobile inventors leads to the acquisition of industry wide 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.

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us to believe that any learning effect that could result from inexperienced inventors is removed after considering the growth of the firm.

Table 4.4: Coefficient estimates of robustness checks and placebo test

	Model 5	Model 6	Model 7	Model 8	Model 9
Hired from cited		0.365***	0.136	0.275***	0.075***
		(0.081)	(0.110)	(0.083)	(0.025)
Hired from others		0.009	0.005	0.042**	0.036***
		(0.022)	(0.034)	(0.017)	(0.009)
Initial hiring from cited * spinoff		0.147	-0.058	0.178	
		(0.212)	(0.343)	(0.183)	
Initial hiring from others * spinoff		-0.066	0.031	-0.053	
		(0.108)	(0.091)	(0.094)	
Initial hiring from cited * (1-spinoff)		-0.080	0.032	-0.117	
		(0.120)	(0.134)	(0.111)	
Initial hiring from others * (1-spinoff)		0.093**	0.028	0.081*	
		(0.047)	(0.052)	(0.047)	
Log (Stock IC patents cited firm)	0.983***	0.962***	0.988***	0.672***	0.582***
	(0.021)	(0.021)	(0.021)	(0.046)	(0.026)
Log (Stock IC patents citing firm)	0.720***	0.738***	0.742***	0.731***	0.497***
	(0.050)	(0.059)	(0.055)	(0.052)	(0.026)
Nr. Patents citing firm	0.004	0.004	0.007**	0.005**	0.006***
	(0.007)	(0.006)	(0.003)	(0.002)	(0.001)
Local not SV	0.259*	0.163	0.276**	0.235***	
	(0.146)	(0.142)	(0.128)	(0.090)	
Local SV	0.650***	0.462***	0.626***	0.158	
	(0.141)	(0.125)	(0.133)	(0.168)	
Hired from cited * leader		-0.179	0.038	-0.117	
		(0.124)	(0.164)	(0.090)	
Hired from leaders – hired from		0.074	0.159***	0.032	
cited * leader		(0.046)	(0.055)	(0.038)	
Hiring of inexperienced inventors	0.002	0.001			
	(0.003)	(0.003)			
Recent spinoff (10 years)		0.727**		0.621*	
		(0.370)		(0.344)	
Constant	-9.157***	-9.220***	-9.335***	-7.674***	-5.346***
	(0.207)	(0.213)	(0.207)	(0.274)	(0.145)
Observations	49243	49243	38096	38131	9529
Cited firm fixed effects	No	No	No	Yes	No
Dyads fixed effects	No	No	No	No	Yes

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

In the base models we include several control variables to account for heterogeneity across cited firms. To provide a more flexible way of addressing the variation in the value of different firms' patents, and thus on the likelihood of a firm's patents getting cited, in Model 7 we estimate the analog to Model 4 using cited firm fixed effects. Observations where the cited firm is never cited are dropped, which excludes 11,112 observations that correspond to 30 firms. The coefficient estimates reported in Table 4.4 are qualitatively similar to those of Model 4. The differences are that the coefficient estimates of *Hiring from others* and *Local nSV* are now significant, while that of *Local SV* is no longer significant. Finally, the coefficient estimate of *Hiring from leader – hiring from cited * leader* now decreases and drops out of significance. The magnitude and significance of our main explanatory variables remain consistent with the hypotheses.

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 our 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 *Hiring from cited* and *Hiring from others* coefficients while maintaining the control variables[59]. The

[59] 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

coefficient estimates of both hiring count variables, reported as Model 8 in Table 4.4, 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 if we consider 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.

4.6 Discussion

We propose 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 wide knowledge inventors accumulate throughout their careers. Incumbents and new firms will differ in their interest for firm specific and industry wide knowledge. The acquisition of industry wide 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

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considering that most of the relationship between parents and spinoffs is now captured by the dyad fixed effect.

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 wide knowledge. Consistent with our theory, spinoffs only benefit from the mobile inventor's previous employer's knowledge if he is hired from the parent. Inventors hired by new firms from unrelated entities contribute mostly by bringing in industry wide knowledge. In terms of economic importance, each mobile inventor contributes more with firm specific knowledge than with industry wide knowledge. However, the latter is derived 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 inventors who are hired from other firms. This makes the overall acquisition of industry wide knowledge economically significant for recent entrants. In the case of incumbents, we found that they only acquire disciplinary knowledge when the inventor is hired from a leading firm. We find evidence, although it is limited, that when the inventor is hired from a leading firm, the amount of knowledge transferred directly from the inventor's previous employer is no different, or even smaller, than the amount of knowledge transferred by inventors hired from lesser firms. The key contribution of inventors hired by incumbents from the leading firms is the acquisition of industry wide knowledge.

These results provide an interesting interpretation of the benefits recent entrants in Silicon Valley enjoyed. The larger availability of workers in this cluster will make it easier for recent entrants to put together their founding team. The contribution of most of these inventors is industry wide knowledge and thus should be highly substitutable. Moreover, the inventors who apparently contributed the most in terms of industry wide knowledge

came from large patenters, all of which were located out of Silicon Valley. While the availability of workers may largely ease the entry of startups, it does not seem to provide a sustainable competitive advantage. Any 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 there were 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 make 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. This could also shed light on why almost none of the spinoffs from incumbents located in other regions chose to enter in Silicon Valley. Conceivably the gains they could get from locating in Silicon Valley were not enough to outweigh the benefits from staying close to the parent.

As with other studies based on patent data, our results are not exempt from potential problems. While it is reasonable that young firms hire experienced inventors to

acquire disciplinary 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 et al. 2009) and aggressive intellectual property litigation (Agarwal et al. 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 & Lissoni 2006). While we found support for this theory, our results 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 & Klepper 2010). Spinoffs tend to locate close to the parent, especially if they plan to compete at the forefront of their field (Berchicci, King & Tucci 2011). If the only way spinoffs tapped into their parents' knowledge was 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.

5 Summary and Conclusions

This dissertation systematically studies inventor mobility in the semiconductor industry and its role on the diffusion of knowledge. The dissertation begins with an analysis on the importance of experienced inventors for the entry of spinoffs. The semiconductor industry is famous for being clustered in Silicon Valley, a region that is also distinguished for its high rate of worker mobility. The first part of this dissertation argues that this regional pattern of worker mobility is strongly related to the entry of spinoffs. Many firms were constantly being created in Silicon Valley, and to get started they hired many experienced inventors from other local firms. This process led to elevated rates of mobility in the region. After controlling for the movements of inventors to new firms, mobility rates in Silicon Valley are only slightly higher than in other regions.

This raises questions about how and to what extent incumbents benefit from being located in this cluster. The benefits of clustering that materialize through inventors' changing jobs more frequently will be enjoyed mostly by new entrants rather than by incumbents. It also begs us to consider what leads to spinoff entry. The process that generates spinoff entry is what ultimately drives the emergence of a cluster. Clusters can facilitate firm entry, as the availability of inventors is important to new firms. Nonetheless, entry was high in Silicon Valley from early on, and these entrants staffed their initial needs with workers brought from other regions. The rest of the dissertation delves on providing a better understanding of what entrants are looking for from moving inventors. This is necessary to understand the process that leads to spinoff entry and the importance of the availability of inventors in fostering this process.

The third chapter attempts to determine the motivations firms have to hire experienced inventors and the characteristics of the inventors who are more likely to get

hired away. This chapter argues that incumbents, recent entrants, and spinoffs have very different goals in mind when hiring seasoned workers. While incumbents hire workers who are a good fit to their pursuits, spinoffs hire many inventors who are knowledgeable in the idea that led to the spinoff from their parents. In the case of inventors hired by recent entrants (from firms other than their parents), there does not seem to be any particular feature that distinguishes them. This is intriguing, as new firms are hiring many inventors, but their characteristics do not suggest any particular motivation. Only inventors hired from the parent have a clear goal, which is providing knowledge that is related to the initial undertakings of the new firm.

The last part of the dissertation takes a more detailed view of how firms learn from the inventors they hire. The patterns presented in the previous chapters, namely that incumbents hire mostly workers with no prior patenting experience, while new firms hire mostly experienced inventors, suggest that there are very different objectives behind this hiring. The central tenet of this chapter is that inventors hired by incumbents, and by recent spinoffs from their parent, contribute mostly by bringing in knowledge that was developed by their previous employers. In contrast, the main contribution of inventors hired by recent entrants is increasing the ability of the receiving firm to cite patents from any firm in the industry (note this includes inventors hired by recent spinoff from firms other than their parent).

This result suggests that many of the inventors hired by new firms are highly substitutable. The only inventors who are indispensable are those hired from the parent of a spinoff. This may help to explain why spinoffs outside of Silicon Valley choose to locate closer to their parent, rather than to move to Silicon Valley and benefit from the greater availability of workers there. It also helps to understand why the firms that entered in

Silicon Valley in the 1960s managed to be successful, despite the fact that the major players of the industry during that period were located on the East Coast. It also emphasizes the role of the idea generation process and its localization. Under this interpretation, what led to the clustering of the industry in Silicon Valley was that many of the key innovations that shaped the integrated circuit arose there. Once the innovators had the idea and a small group of inventors were knowledgeable of it, it was less important how they assembled the rest of their team. Initially, they attracted inventors from other regions. Once the industry clustered, it got even easier to enter in the region, as workers were already available locally. Note that this does not prevent ideas from arising in other regions. When those ideas arise, the same process of initial staffing is at place. The innovator remains local in order to gather his initial core team and then hire other workers with general knowledge about the industry from distant regions if necessary. Not having a base of local general workers certainly raises the cost of entry, but it should not prevent innovators with superior ideas to succeed.

The results presented in this dissertation have interesting policy implications. Firms located in clusters have long been thought to enjoy a series of advantages. With respect to knowledge diffusion, it is frequently argued that the greater mobility of workers in clusters helps firms located there to stay at the forefront of technology. The results presented in this dissertation provide a better understanding on how this benefit materializes, who enjoys it, and how it influences firm entry and success. As most of the increased mobility in Silicon Valley corresponds to inventors from incumbents to recent entrants, it is new firms that capture the benefits brought by enhanced worker mobility. In this context incumbents act as training grounds for inventors who are later hired away by entrepreneurial firms. In order to be advantageous for incumbents who remain in the cluster, there must be other benefits, such as attracting a broad base of new talent or

having a larger pool of inventors to choose from in the instances they do hire experienced workers.

Another interesting policy dimension to consider is how recent entrants use the knowledge of the workers they hire. While the learning-by-hiring literature has emphasized the transfer of knowledge from the worker's previous employer to his new firm, the results presented in this dissertation suggest that a great share of the inventors hired by entrants were brought in for their general knowledge about the industry. This could affect the interpretation of the cost and benefits of non-compete covenants. Firms often ask employees to sign these contracts in order to prevent them from moving to a competitor. The main motivation is to prevent the leakage of information to competing organizations, and almost all states allow them, to different extents, in order to incentivize investment on research and development. While the concern is valid, the non-compete instrument also prevents workers from moving to new firms and providing their expertise on non-proprietary knowledge, which could hinder firm entry. The idea that leads to the creation of a new firm is unlikely to come from general knowledge, but facing difficulties with hiring experienced workers raises the cost of entry and thus jeopardizes the firm's probability of success. Designing mechanisms that protect intellectual property and trade secrets while allowing inventors to move to new firms would provide a better balance without sacrificing social benefits. Policy makers must ponder the protection of intellectual property with the availability of inventive labor.

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Appendix A: Location, years in industry, heritage, assigned patents, and rate at which employees changed employers of firms in sample.

Company Name	Region	Entry/Exit*	Parent	Patents-inventors 70-87**	Nr. Obs.	Mob. Rate
RCA	NY	1950/1986		2593	1663	1.3%
Texas Instruments	DALLAS, TX	1952/2002		2559	1923	2.4%
Motorola	PHOENIX, AZ	1958/2002		2322	1575	3.0%
Fairchild	SF	1957/1987		573	346	9.0%
National	SF	1967/2002	Fairchild	503	327	10.4%
AMD	SF	1969/2002	Fairchild	419	290	5.5%
Harris	MELBOURNE, FL	1967/2002		409	277	4.7%
Signetics	SF	1961/1992	Fairchild	369	227	7.5%
Intel	SF	1968/2002	Fairchild	361	236	11.4%
Raytheon	BOS	1950/1997		295	145	2.8%
Mostek	DALLAS, TX	1969/1985	Texas Instruments	233	157	9.6%
General Instrument	NY	1960/2000		141	85	11.8%
Sprague	BOS	1955/2002		130	69	8.7%
International Rectifier	LA	1947/2002		102	65	1.5%
Monolithic Memories	SF	1969/1987		82	63	7.9%
American Microsystems	SF	1966/2002		68	31	19.4%
Analog Devices	BOS	1965/2002		59	41	2.4%
Siliconix	SF	1962/1998	Texas Instruments	58	44	2.3%
Intersil	SF	1967/1988		38	16	31.3%
Standard Microsystems	NY	1971/2002	General Instrument	33	21	4.8%
Precision Monolithics	SF	1969/1990	Fairchild	29	18	5.6%
Seeq Technology	SF	1981/1999	Intel	29	24	20.8%
Xicor	SF	1978/2004	Intel	27	24	4.2%
Solid State Scientific	NORRISTOWN, PA	1969/1984		22	14	7.1%
Zilog	SF	1974/2002	Intel	21	10	40.0%
Unitrode	BOS	1981/1999		19	13	0.0%
Cypress Semiconductor	SF	1982/2002	AMD	17	8	12.5%
Linear Technology	SF	1981/2002	National	17	12	0.0%
Solitron	TAPPAN, NY	1965/2002		17		
TriQuint	PORTLAND, OR	1985/2002		17	11	0.0%
Altera	SF	1983/2002		16	16	0.0%
Teledyne	SF	1961/2002	Fairchild	16	9	33.3%
Actel	SF	1985/2002	Intel	15	15	0.0%
Supertex	SF	1976/2002	Fairchild	15	13	7.7%
LSI Logic	SF	1980/2002	Fairchild	13	12	8.3%
Xilinx	SF	1984/2002	Zilog	13	13	0.0%
Exel Microelectronics	SF	1983/1998	Seeq Technology	12	6	16.7%
Maxim	SF	1983/2002	Applied Micro Circuits	12	11	0.0%
Dallas Semiconductor	DALLAS, TX	1984/2001	Mostek	10	10	0.0%

Semi	PHOENIX, AZ	1969/1979		10	4	25.0%
Lattice	PORTLAND, OR	1983/2002	Intel	9	9	0.0%
EG&G Reticon	SF	1971/2002	Fairchild	7	3	0.0%
VLSI Technology	SF	1979/1999	Synertek	7	3	33.3%
Micro Power Systems	SF	1971/1994	Intersil	6	5	0.0%
Synertek	SF	1973/1985		6	1	100.0%
Applied Micro Circuits	SF	1979/2002	American Microsystems	5	4	100.0%
Gigabit Logic	LA	1981/1991		5	1	0.0%
Avantek	SF	1965/1991		4		
International Microelectronic	SF	1981/2002	American Microsystems	4		
PMC-Sierra	SF	1984/2002	National	4	2	50.0%
Sipex	BOS	1965/2002		4		
Atmel	SF	1984/2002	Seeq Technology	3		
Transitron	BOS	1952/1986		3	1	100.0%
Chips and Technologies	SF	1984/1997	Seeq Technology	2	2	0.0%
Inselek	NY	1970/1975	RCA	2	1	100.0%
Integrated Device Tech	SF	1980/2002		2		
Telmos	SF	1981/1986	Semi Processes	2		
Electronic Arrays	SF	1967/1979		1		
Exar	SF	1971/2002	Signetics	1	1	0.0%
International Microcircuits	SF	1972/2001	Fairchild	1	1	0.0%
Nitron	SF	1972/1985		1		
Silicon General	LA	1969/2002		1	1	100.0%
ACC Microelectronics	SF	1987/2002	Intel	****		
Alliance Semiconductor	SF	1985/2002		****		
Anadigics	SF	1985/2002		****		
Bipolar Integrated Tech	PORTLAND, OR	1983/1996		****		
California Micro Devices	SF	1980/2002		****		
Catalyst Semiconductor	SF	1985/2002	Exel Microelectronics	****		
Cirrus Logic	SF	1981/2002		****		
Elantec	SF	1983/2002	National	****		
Integrated Circuit System	NORRISTOWN, PA	1976/2002	General Instruments	****		
Level One Communications	SACRAMENTO, CA	1985/1999	Intel	****		
Logic Devices	SF	1983/2002	Applied Micro Circuits	****		
Micrel	SF	1978/2002	Fairchild	****		
Micro Linear	SF	1983/2002	Exar	****		
Micron Tecnhology	BOISE, ID	1978/2002	Mostek	****		
Paradigm	SF	1987/2002		****		
S-MOS Systems	SF	1983/***	Micro Power Systems	****		
Saratoga	SF	1985/1989		****		
Synergy	SF	1987/***	AMD	****		
Vitesse	LA	1984/2002		****		

* Exit dates were traced up to year 2002. Firms that were active by the end of the period are reported as exiting in 2002.
** A patent with 3 inventors corresponds to 3 patents-inventors.
*** Unknown exit date.
**** Firms with patents after 1987 only.

Appendix B: Description and summary statistics of variables used in empirical models of Chapter 4.

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 inventor 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.