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Cristobal Cheyre, Steven Klepperdeceased, Francisco Veloso

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Spinoffs and the Mobility of U.S. Merchant Semiconductor Inventors

Cristobal Cheyre
Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, Pennsylvania 15213;
Católica Lisbon School of Business and Economics, Universdidade Católica Portuguesa, 1649-023 Lisbon, Portugal; and
School of Engineering, Pontificia Universidad Católica de Chile, Santiago, Chile, ccheyre@ing.puc.cl

Steven Klepper
deceased
Formerly of the Department of Social and Decision Sciences, Carnegie Mellon University, Pittsburgh, Pennsylvania

Francisco Veloso
Católica Lisbon School of Business and Economics, Universdidade Católica Portuguesa,
1649-023 Lisbon, Portugal, fveloso@ucp.pt

Data on inventors and assignees of patents are 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 noncompete covenants may influence spinoff entry, but spinoffs promote mobility even in the absence of those conditions. Because 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.

Keywords: inventor mobility; spinoffs; clusters; agglomeration economies
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1. Introduction

Knowledge spillovers have long been viewed as a primary force solidifying industry clusters. Marshall (1890) long ago remarked that when firms in the same industry locate close to each other, it is as if knowledge is in the air for all to learn, making the firms stronger competitors. Recent studies of patent citations suggest that knowledge does diffuse locally (Jaffe et al. 1993), namely through mobile inventors (Breschi and Lissoni 2006). The diffusion tends to be localized because inventors do not generally move far when they change employers (Breschi and Lissoni 2006). To the extent that industry clusters promote worker mobility by making it easier for workers to change jobs, they will also foster local knowledge diffusion. As a result, incumbent firms in clusters will be better able to stay close to the technological frontier in their industry, enabling them to be superior performers. This will impart a self-reinforcing character to clusters (Duranton and 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, 2010), tires (Buenstorf and Klepper 2009), semiconductors (Klepper 2007, 2010), disk drives (Christensen 1993, McKendrick et al. 2000, Franco and Filson 2006), and biotechnology (Mitton 1990, Romanelli and 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 that spinoffs hire disproportionately 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. 34–35). Job mobility and knowledge diffusion have been of particular interest in this industry (Angel 1989, Almeida and Kogut 1999, Almeida et al. 2003, Rosenkopf and Almeida 2003, Song et al. 2003, Agarwal et al. 2009, Corredoira and Rosenkopf 2010). The 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 over a period of time that encompasses the birth and growth of the cluster. 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 United States. Compared with inventors located elsewhere, the mobility rate of inventors in Silicon Valley is about three 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 big 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. Although we find that inventor mobility is higher in Silicon Valley, after taking into account firm factors, especially the size of patenting and the flow of patenters from incumbents to new entrants, no statistically significant difference is left between the mobility of patenters in Silicon Valley and elsewhere. These findings suggest that any greater knowledge diffusion brought about by higher rates of job mobility in Silicon Valley was due to knowledge flowing mainly from incumbents to entrants. These results also contrast with prior works that attribute the higher mobility of workers in Silicon Valley to the clustering of the industry in this region or to the ban on the enforcement of noncompete covenants in the state of California (Gilson 1999, Fallick et al. 2006).[1] In light of these differences, we ponder how the spinoff process contributed to the clustering of the industry and how the availability of workers or the ban on noncompete covenants facilitates the entry of spinoffs. Although we cannot unequivocally disentangle whether the entry of spinoffs in Silicon Valley is driven by agglomeration economies and the inability to enforce noncompete covenants, we find evidence that suggests the staffing process of new firms we describe is independent of these factors. Mobility in Silicon Valley is higher early on, when the industry was not yet clustered in the region and many spinoffs were being formed. Additionally, the influence of spawning on a firm's inventor mobility and on the mobility of inventors of nearby firms is observed for firms both in and outside of Silicon Valley. In fact, spinoffs outside of Silicon Valley hire even more inventors from their parents than do spinoffs in Silicon Valley.

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

2. Spinoff Entrants' Hiring Choices and Their Effect on Inventor Mobility

The semiconductor industry began after the invention of the transistor at Bell Labs in 1947. The first firm in 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 Advanced Micro Devices (AMD), which were founded in 1967, 1968, and 1969, respectively (Klepper 2009).

In the late 1960s, when our data set begins, 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 U.S. semiconductor industry. Toward the late 1980s, the end of our data set, more than 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 (Saxenian 1994, Almeida and Kogut 1999). Industry clustering and nonenforceable noncompete covenants have previously been considered as explanations for these observations (Gilson 1999, Fallick et al. 2006). Yet the huge number of spinoffs in the region is also likely to have influenced

[1] Marx et al. (2009) also found that a change in Michigan's law allowing noncompete covenants to be enforced decreased the mobility of inventors, and Garmaise (2011) found similar effects on the mobility of executives in other states where the law on the enforceability of noncompete covenants changed.

this heightened mobility, because 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. Although spinoffs are nominally separate entities with no formal connection to the parent, they inherit technical knowledge (Klepper and 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 (Franco and Filson 2006, Buenstorf and Klepper 2009). 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 and Nitzan 1983, Klepper and Sleeper 2005, Cassiman and Ueda 2006, Klepper and Thompson 2010). In such cases, the founder's former coworkers 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 preentry knowledge about the region (Buenstorf and Klepper 2010). This proximity further helps the process of hiring inventors from the parent.

Spinoffs probably cannot 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, because their social networks and knowledge about the region will make it easier to find prospective employees (Buenstorf and 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 parent, they turn to other local incumbents. Thus, we hypothesize the following.

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. 34–35). Almeida and Kogut (1999) documented a rate of labor mobility in Silicon Valley roughly three times that of other regions. Semiconductor firms located in Silicon Valley also had a spinoff rate roughly five times higher than firms elsewhere, and almost all of those 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 and Filson 2006, Buenstorf and Klepper 2009). As noted above, spinoffs stay close to their parents (Buenstorf and 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 noncompete agreements (Gilson 1999, Marx et al. 2009) and a recognized entrepreneurial culture (Saxenian 1994).

Outside 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 (TI) in Texas. Although these firms had a few spinoffs, including some that got to be leading firms, their spawning levels were negligible compared with 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 Valley. Spinoffs outside of California would be likely to face difficulties in hiring inventors from their parents as a result of enforceable noncompete 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 et al. (1990), as well as Davis et al. (1998), found that the mobility rate of U.S. workers within industries is lower in larger firms. Specifically for scientists and engineers, Elfenbein et al. (2010) reported that job turnover declines sharply with firm size. Similarly, in a survey of semiconductor engineers, Angel (1989) found that job tenure is negatively related to the 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 competencies from which to hire inventors. As a result, one could expect spinoffs outside 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 the following.

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 that 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 and 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 and Sorenson 2005). This will be especially relevant for workers of the parent firm, where the spinoff founder would have a variety of connections among coworkers. 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 lead 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.*

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 into 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 issued from 1970 to 2002 in five main semiconductor classes were downloaded from the United States Patent and Trademark Office website, and the firm identifiers[2] in the 2004 update of the National Bureau of Economic Research (NBER) database (Hall et al. 2001) were used to determine which of these patents were assigned to the ICE firms. The patent class numbers 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).[3] These patents accounted for between

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

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

60% and 70% of the patents issued to the Silicon Valley semiconductor producers on our list, which were mainly semiconductor specialists. In contrast, for larger diversified firms such as 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, because we will not be able to explain the mobility of other inventors even if it was related to the formation of (nonsemiconductor) spinoffs.

Eighty-one of the ICE firms in our data set 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 et al. (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 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 and adjusted moves accordingly.[6] A small number of other cases were more complicated and were adjusted on an individual basis.[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 0.25 years *before* date 1.[8] This suggests that date 1 is a pretty good estimate of when the inventor moved. Accordingly, we date the year of the move based on date 1 unless the inventor applied for a later

[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, from Michael J. Allen, who was granted 15 patents between 1988 and 1995 that were assigned to Intel. That the Intel patents followed quickly those of AMD, that both Intel and AMD are semiconductor producers, and the closeness of the names led us to classify these two inventors as the same person.

[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.

[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 1966–1994, 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 coinventor whose name was listed first, which may have played a role in the assignment of the patent. In such cases, we assumed that the inventor had always worked at Motorola and the patent assigned to Fairchild was due to the coinventor.

[8] Among the 13 moves that we could date, 3 occurred within three years before the last patent at the prior employer, 7 in the same year as the last patent at the prior employer, and 3 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 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 research and development 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 the longest time between an inventor's consecutive patents at different firms of any inventor who moved in our sample.

Table 1 Mobility Rate of Inventors in Silicon Valley vs. 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 (%)
SV	1,793	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	6,086	173	2.8	759	25	3.3	1,174	37	3.2	1,444	38	2.6	1,785	61	3.4	924	12	1.3
Total	7,879	336	4.3	868	40	4.6	1,442	54	3.7	1,797	61	3.4	2,453	135	5.5	1,319	46	3.5
Ratio SV/Others			3.2			4.2			2.0			2.5			3.2			6.6

Notes. The sample corresponds to all patents in five main integrated circuit 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. SV, Silicon Valley.

nonsemiconductor 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) 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 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 1 who moved three times.

4. Broad Patterns

Before considering the mobility of inventors, we check how our data set conforms to previous findings in the same industry. Table 1 reports the mobility rate of inventors in Silicon Valley[9] and elsewhere for various time periods. The mobility rate is 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).

We found it interesting that 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, because the industry was much less clustered in Silicon Valley before 1971 than after. 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 noncompete covenants rather than the clustering of the computer industry in Silicon Valley and elsewhere in California.

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 inventors. Six of the 10 involved moves from Fairchild to one of its spinoffs, and 2 others involved a move from Fairchild to American Microsystems, which was founded by a prior Fairchild employee who had left Fairchild to cofound 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]

[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 it was not, it was often due to an employer filing a patent in the inventor's name after he had moved to a new employer.

[10] This difference is significant at the 0.001 level based on Fisher's exact test.

[11] These differences are significant at the 0.01 and 0.05 levels, respectively, based on Fisher's exact test.

Table 2 Overall Inventor Mobility Rate for Firms with More than 100 Observations

Company name	Observations	Movements	Mobility 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	1,575	48	3.0
Raytheon Semiconductor	145	4	2.8
Texas Instruments	1,923	47	2.4
RCA	1,663	21	1.3

Notes. The sample corresponds to all patents in five main integrated circuit 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.

A broader indicator of the influence of spinoffs on mobility is conveyed by Table 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, Texas. 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 (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 the appendix 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 relative to their size. RCA had the fewest spinoffs, with only one, and the lowest mobility among these firms. TI and Motorola had three and two 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 3 early major spinoffs from Fairchild (National, Intel, and AMD), the 34 later spinoffs in Silicon Valley with parents in our sample, and the 7 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 parent

[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.

[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.

Table 3 Accounting for Inventor Movements

	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 (%)
Panel I: Overall mobility rates																		
SV	1,793	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	6,086	173	2.8	759	25	3.3	1,174	37	3.2	1,444	38	2.6	1,785	61	3.4	924	12	1.3
Total	7,879	336	4.3	868	40	4.6	1,442	54	3.7	1,797	61	3.4	2,453	135	5.5	1,319	46	3.5
Ratio SV/Other regions			3.2			4.2			2.0			2.5			3.2			6.6
Panel II: Excluding flows from parent to recent spinoffs																		
SV	1,793	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	6,086	161	2.6	759	21	2.8	1,174	36	3.1	1,444	35	2.4	1,785	57	3.2	924	12	1.3
Total	7,879	286	3.6	868	30	3.5	1,442	49	3.4	1,797	53	2.9	2,453	115	4.7	1,319	39	3.0
Ratio SV/Other regions			2.6			3.0			1.6			2.1			2.7			5.3
Panel III: Excluding flows to recent entrants in the same region																		
SV	1,793	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	6,086	158	2.6	759	21	2.8	1,174	36	3.1	1,444	34	2.4	1,785	55	3.1	924	12	1.3
Total	7,879	236	3.0	868	24	2.8	1,442	46	3.2	1,797	49	2.7	2,453	86	3.5	1,319	31	2.4
Ratio SV/Other regions			1.7			1.0			1.2			1.8			1.5			3.7
Panel IV: Excluding flows to recent entrants in other regions																		
SV	1,793	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	6,086	122	2.0	759	13	1.7	1,174	29	2.5	1,444	30	2.1	1,785	41	2.3	924	9	1.0
Total	7,879	193	2.4	868	16	1.8	1,442	39	2.7	1,797	44	2.4	2,453	69	2.8	1,319	25	1.9
Ratio SV/Other regions			2.0			1.6			1.5			1.9			1.8			4.2

Notes. The sample corresponds to all patents in five main integrated circuit (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. SV, Silicon Valley.

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

5. Statistical Analysis

We begin with a simple accounting of the aggregate moves of inventors and the effect of these moves on the relative mobility of Silicon Valley inventors. Panel I of Table 3 reproduces Table 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 §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.

As stated in Hypothesis 1B, Silicon Valley firms were also expected to have higher mobility as a result of a greater number of spinoffs from other local firms. In panel III of Table 3, we remove all inventor moves to other local entrants (spinoffs or otherwise) in their first five years. Specifically, the 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 hardly changes, 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.

[14] These percentages are not significantly different at the 0.05 level based on Fisher's exact test.

[15] For example, in Silicon Valley there were 163 observations out of a total of 1,793 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 equals 7.0% of the original 1,793 observations. The other entries in panel II have been computed in the same way.

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 of Table 3, 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 data set, 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 data set, 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 data set 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 4.

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 equals 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 ratio reported in Table 1, where the overall inventor mobility rate of Silicon Valley inventors was 3.2 times higher than the overall mobility rate of inventors in other regions.

Model 2 adds controls for characteristics of inventors and whether the inventor's firm is acquired. Palomeras and Melero (2010) found that IBM 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*, *Coinventors*, 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, *Coinventors* is the average number of coinventors 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 whether acquired firms have greater inventor turnover, which might be expected if acquisitions lead to consolidations and changes in firm strategies (Ernst and Vitt 2000), we include a dummy variable, *Acquisition*, equal to 1 if firm A was acquired within three years of date 1 and equal to 0 otherwise. This variable is also interacted with the variable *Recent patents* to test whether acquisitions particularly increase the turnover rate of less productive inventors. Last, *Prior move*, which equals 1 if the inventor moved prior to the patent at firm A and equals 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 that 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 coinventors 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

[16] Citations were obtained from the NBER patent citations database. Because this database contains only 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.

Table 4 Estimates for the Likelihood of an Inventor Move to Another Firm

	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)
Coinventors		−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	7,879	7,879	7,879	7,879	7,879	7,879	7,879
Pseudo-R^2	0.040	0.099	0.105	0.106	0.106	0.106	0.120
Log likelihood	−1,333	−1,252	−1,243	−1,242	−1,242	−1,241	−1,222

Notes. The sample corresponds to all patents in five main integrated circuit (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. The dependent variable is a dummy equal to 1 if the assignees of patents are different in observation. All variables are defined with respect to the first patent of the observation (assignee and time of application). Robust standard errors in parentheses.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

but *Tenure* being significant. Inventors whose firms are acquired are more likely to move, particularly the 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 states 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 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 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.

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* × *Silicon Valley* 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 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* drops to 0.207, which implies a probability of moving relative to not moving of 1.23, and it 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*

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

[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 latter allowed to affect inventors at all firms), and interaction effects in nonlinear models depend on the values of the explanatory variables in complex ways (Ai and Norton 2003). To circumvent this awkwardness, we estimated Model 5 (and Model 6) as a linear probability model. 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.

Table 5 The 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 5 years	After 5 years	First 5 years	After 5 years	First 5 years	After 5 years	First 5 years	After 5 years	First 5 years	After 5 years
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/STM	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

Notes. All firms with an dash ("—") in the first five years fields entered in a period for which we do not have information on patents. IC, integrated circuit; UTC/STM, United Technologies Corporation/STMicroelectronics.

of SVEntrants 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 in his survey of semiconductor engineers that large incumbents do not usually rely on external sources when hiring inventors. 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 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 5 largely conform to our argument. The top six firms in terms of gross outflow of workers are TI, Motorola, National, Fairchild, Intel, 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 started 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 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. They subsequently hired more inventors without prior patents and lost more inventors to other ICE firms in our sample.

6. Robustness Tests

We performed a series of robustness tests of our estimates. First, we explore whether 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 on movements to a restricted set of firms could drive our results, and we 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.

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

Table 6 Estimates for the Likelihood of an Inventor Move to Another Firm: Robustness Checks

	Model 8 (patent 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 1975*						0.151
						(0.444)
Silicon Valley × *From 1976*						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 × *Silicon Valley*			0.339***			
			(0.050)			
Number of spinoffs × (1 − *Silicon Valley*)			0.391	0.390		
			(0.298)	(0.297)		
Number of spinoffs × *Silicon Valley* × *Up to 1975*				0.349***		
				(0.059)		
Number of spinoffs × *Silicon Valley* × *From 1976*				0.333***		
				(0.059)		
Number of SVEntrants × *Silicon Valley*	0.043**	0.017	0.032**	0.033**		0.025*
	(0.020)	(0.011)	(0.013)	(0.016)		(0.013)
Number of SVEntrants × (1 − *Silicon Valley*)	0.021	0.004	0.024			0.024
	(0.028)	(0.017)	(0.022)			(0.019)
Number of SVEntrants × *Silicon Valley* × *Up to 1975*					−0.000	
					(0.045)	
Number of SVEntrants × *Silicon Valley* × *From 1976*					0.026**	
					(0.012)	
Number of SVEntrants × (1 − *Silicon Valley*) × *Up to 1975*					0.039	
					(0.036)	
Number of SVEntrants × (1 − *Silicon Valley*) × *From 1976*					0.027	
					(0.020)	
Other independent variables and controls included *Tenure*, *Recent patents*, *Coinventors*, *Self-citations*, *Acquisition*, *Acquisition* × *Recent patents*, *Prior move*, *Movers from parent to spinoff*, log(*Firm patents*) × *Silicon Valley*, log(*Firm patents*) × (1 − *Silicon Valley*)						
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	7,347	8,340	7,879	7,879	7,879	7,879
Log likelihood	−897.4	−2,287	−1,222	−1,222	−1,222	−1,222
Pseudo-R^2	0.095	0.105	0.120	0.120	0.120	0.120

Notes. Robustness tests of models presented in Table 4 are shown. Model 8 (patent gap test) is analogous to Model 7, but eliminating observations for which more than six years elapsed between the application of the first and second patent. Model 9 (extended sample test) is analogous to 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. Robust standard errors in parentheses.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

six. For the sake of brevity, only the analog of Model 7 is presented as Model 8 in Table 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 with Models 4–7.

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 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 as a result of the increase in the number of observations).

The empirical analysis presented in §5 supports our hypothesis that spinoffs draw many inventors from their parents and other local firms during their first years and that these movements account for most 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 because 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 five parents located in other regions spawned 10 firms. Although 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 6 shows that the coefficient of *Number of spinoffs* is larger for firms outside of Silicon Valley than for firms in Silicon Valley, although not significant. This result is in line with the idea that spinoffs outside of Silicon Valley rely more heavily on their parents as hiring sources of new inventors than spinoffs elsewhere, which was the basis for Hypothesis 2.

The differences we find between firms located in and outside of Silicon Valley seem at odds with previous literature on the effects of noncompete covenants over inventor mobility. The inability to enforce noncompete agreements in Silicon Valley is believed to have faciliated the mobility of inventors and the clustering of the industry there (Gilson 1999, Fallick et al. 2006, 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 noncompete 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 noncompete agreement, or the parent simply was not interested in enforcing the agreement. If the noncompete agreement did not 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 noncompete agreements 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 noncompete agreements 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 spinoff entrants, 14 of them in Silicon Valley and 6 in other regions. After 1975, there are 33 spinoff entrants, of which 29 are in Silicon Valley and 4 elsewhere. In Model 11 of Table 6 we estimate the *Number of spinoffs* $\times$ *Silicon Valley* coefficient separately for spinoffs that enter up to 1975 and for those that enter later. Although we cannot 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 estimates the effect of *Number of SVEntrants* 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, whereas the coefficient of the effect over firms out of Silicon Valley is the largest. After 1975, the coefficients for firms in and outside of Silicon Valley become similar. Although the only combination that is statistically significant is the coefficient of *Number of SVEntrants* $\times$ *Silicon Valley* $\times$ *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 inventors from other regions. Finally, in Model 13 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 inventor mobility increased as the industry clustered, although both dummies are not significant.

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 and Strange 1990, Duranton and Puga 2004). Greater worker mobility can also speed up the diffusion of knowledge across firms (Almeida and Kogut 1999, Breschi and Lissoni 2006), making it easier for colocated 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 and Puga 2004). In this section we explore how our findings relate 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 holdup problems (Duranton and Puga 2004). Models that explain how these benefits materialize rely on inventor mobility to different extents. In the analysis presented in §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, Helsley and Strange's (1990) model on matching 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 competiors. This leads to an increase in overall productivity as a result of 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 benefit through this mechanism from being located in a cluster.

Although 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 in the probability of finding a good match as a result of clustering are based on matching functions that depend on the number of job seekers and the number of positions available (Duranton and Puga 2004). The key advantage of clusters in these models is the variety of workers available. Although incumbents may not be firing and hiring experienced inventors 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 mechanism 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) found that larger organizations hired many engineers right out of college. We do not have information on how many of these engineers stayed with their initial employers. Nonetheless, models of labor turnover propose that when the abilities of workers are uncertain, as in the case of hiring new graduates, firms hire many employees and retain only those that are good fits (Jovanovic 1979, Topel and Ward 1992). Following this logic, incumbents located in a cluster will be desirable first employment places for graduates looking to access other opportunities that exist in the cluster, 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 noncodifiable knowledge is embedded in employees. Competitors wanting to acquire this knowledge may hire these workers 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 such as those of Cooper (2001) and Combes and Duranton (2006) find conditions where high labor mobility may be beneficial for colocated 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 as a result of labor poaching. Our results suggest that the costs of labor poaching are suffered by incumbents, whereas the benefits of labor pooling are reaped by spinoffs, which makes the equilibrium proposed by these models unlikely. 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 homogeneous 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 whether agglomeration economies raise worker mobility at all firms or whether they promote mobility by facilitating the entry of new ventures is challenging. The key question is whether agglomeration economies spur spinoff entry by themselves, or if they facilitate 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 spinoff ideas, for example, through peer effects (Nanda and Sørensen 2010), through 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 in the cluster (Kenney and 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.

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 nonlocal 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 nonsemiconductor producers. However, apart from AT&T and IBM, which were large captive producers, the firms included in our sample represent all the major semiconductor innovators in the era we study and thus are 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. Although 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, because it questions how and to what extent clustering and the ban on the enforcement of noncompete agreements foster mobility in the region. Some of the patterns we find are 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 were not 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 noncompete 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 Valley hired more inventors from their parents than spinoffs in Silicon Valley. These patterns do not rule out that agglomeration and the ban of noncompete agreements in California influenced the rate of spinoffs' entry, which they probably 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 and Almeida 2003, Kim and Marschke 2005, Tzabbar 2009, Singh and

[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 although 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.

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, this conceivably comes at the cost of the incumbents who unwittingly serve as training grounds for the initial employees of spinoffs. This is consistent with the results of Agarwal et al. (2009), who found that larger firms in the semiconductor industry are very zealous in protecting their intellectual property 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. Instead, our results suggest that spinoffs, but not 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 and Kerr 2009, Alcácer and Chung 2013), but this advantage becomes less relevant as the firm becomes established. If this is the case, it is intriguing how spinoffs consider this in their location decision. Although 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) reflected on 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. Colocation is socially optimal in the model, but as competition among firms increases, more firms choose not to colocate. 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 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 (2013) findings concerning the importance of skilled labor in the location choice of foreign entrants into the United States.

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 cofounder 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 and Davis 2004). It all began with Fairchild, which was distinctive in terms of both 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, which can also expand the range of activities pursued in a region. Indeed, more work is needed for fully understanding spinoffs and the intricacies of their role in industry clusters. Our findings indicate that, independent of the process that may have spurred the clustering of the semiconductor industry in Silicon Valley, spinoffs were instrumental in the high rate of inventor mobility in Silicon Valley in ways that have not previously been recognized.

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

[22] Consistent with this expectation, Carias and Klepper (2010) found that Portuguese entrants that located close to their parents hired a greater fraction of their initial employees from their parents. They also found 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.

Appendix

Table A.1 Location, Years in Industry, Heritage, Assigned Patents, and Rate at Which Employees Changed Employers

Company name	Region	Entry/exit[a]	Parent	Patents-inventors 1970–1987[b]	No. of obs.	Mobility rate (%)
RCA	NY	1950/1986		2,593	1,663	1.3
Texas Instruments	Dallas, TX	1952/2002		2,559	1,923	2.4
Motorola	Phoenix, AZ	1958/2002		2,322	1,575	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 Electric	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

Table A.1 (Continued)

Company name	Region	Entry/exit[a]	Parent	Patents-inventors 1970–1987[b]	No. of obs.	Mobility rate (%)
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 Technology	SF	1987/2002		****		
S-MOS Systems	SF	1983/[c]	Micro Power Systems	****		
Saratoga Semiconductor	SF	1985/1989		****		
Synergy Semiconductor Corporation	SF	1987/[c]	AMD	****		
Vitesse Semiconductor	LA	1984/2002		****		

Notes. BOS, Boston; LA, Los Angeles; NY, New York; SF, San Francisco. Asterisks (****) denote firms with patents after 1987 only.
[a]Exit dates were traced up to year 2002. Firms that were active by the end of the period are reported as exiting in 2002.
[b]A patent with three inventors corresponds to three patents-inventors.
[c]Unknown exit date.

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Steven Klepper sadly passed away before the latest revision of this work was completed. Testimony of a life committed to his research and scholarly excellence, he was eager to see this work completed to his very last days. Unfortunately, Steven did not get a chance to do this. All ideas expressed in this manuscript are, to the best of our capacity, a loyal reflection of what we had agreed with him. Steven was a true inspiration to all in the profession. With thousands of citations, his work significantly advanced our understanding of how industries and regions develop. But his impact went much beyond the papers. Deeply committed to the highest levels of scholarly work, Steven had a profound influence on generations of students and fellow researchers, whom he constantly challenged to look beyond the traditional assumptions, ask deeper questions, and never settle for less than an important contribution. A loyal and generous person, Steven was a constant source of wisdom, knowledge, and support to all around him. We will dearly miss our friend, colleague, and mentor.

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