Job Hopping in Silicon Valley:

The Micro-Foundations of a High Technology Cluster

Bruce Fallick
Board of Governors Federal Reserve System

Charles A. Fleischman
Board of Governors, Federal Reserve System

James B. Rebitzer
Case Western Reserve University,
The Levy Institute and
The National Bureau of Economic Research

10/23/2003

Abstract

The geographic clustering of firms is a poorly understood feature of market economies. In this paper, we analyze a widely discussed cause of spatial concentration: knowledge spillovers due to employee mobility between firms. Our focus is on the computer industry – particularly on Silicon Valley's computer cluster.

We present a model of innovation and knowledge spillovers in computers and develop three implications from it: (1) a high degree of spatial concentration and high rates of employee "job hopping" between firms are associated with rapid rates of innovation; (2) "non-compete agreements" that inhibit employee movement to competitors will *reduce* spatial concentration and innovativeness; and (3) implications (1) and (2) will generally *not* hold outside of computers.

California differs from other states in that its law makes "non-compete" agreements unenforceable. Combining this fact with new data on inter-firm mobility, we find empirical support for our model.

JEL Classification R12, L63, O3, J63; J48

Introduction

The geographic clustering of firms is a ubiquitous, but poorly understood, feature of advanced economies. Many fundamental issues in economics, such as the role of cities in economic development and the location of production in a global economy, have at their root some theory of spatial clustering. Theories of economic agglomerations are also important in the design of economic policies aimed at stimulating the development of high technology districts.

In the economics literature, explanations for the geographic concentration of firms have focused on "external economies of scale" or equivalently "agglomeration economies". These terms refer to mechanisms that improve the efficiency of production at an individual firm when other related firms co-locate in an area.[1] In this paper we use a new source of data to examine empirically the role of a much-discussed source of "external economies of scale" in a much-discussed industry and economic cluster. Our focus is on the computer industry and the agglomeration economy we investigate is knowledge spillovers due to the easy mobility of skilled employees among firms in Silicon Valley.

Annalee Saxenian was among the first to propose the idea that high rates of job mobility were a source of agglomeration economies in Silicon Valley (1994)[2]. She argued that the sustained high-rates of innovation of computer firms in the Santa Clara valley were the result of two unique aspects of the industrial organization of the region. The first feature was that computer systems manufacturers relied on networks of independent suppliers who specialized in

---

[1] For an excellent and comprehensive review of the literature on geographic clustering see Rosenthal and Strange (2003). Porter (1998) discusses the policy implications of clusters.

[2] Some discussion of mobility preceded Saxenian's work, see for example Angel 1989.

incorporating the latest technological advances into modular components.[3] Modularity increased the rate of technical innovation by allowing rival component manufacturers the freedom to experiment with product design provided that their component conform to design rules that integrated components into the final product.[4] Modularity also forced the various suppliers into a competition to build the latest technology into components [5]

The second key feature of the industrial organization of Silicon Valley was the rapid diffusion of technical knowledge throughout the region. Much of the most valuable knowledge in this industry was acquired informally by hands-on experience and then spread via the easy and rapid movement of employees from one company to another. This knowledge spill-over was further facilitated by the adoption of "open" operating systems (such as Unix) as well as modular component systems.

---

3 "Companies like Sun, Tandem and Mips recognize that the design and production of computers can no longer be accomplished by a single firm: it requires the collaboration of a variety of specialist firms, none of which could complete the task on its own…. These highly focused producers depend on the unparalleled agglomeration of engineers and specialist suppliers of materials, equipment and services in Silicon Valley, and on the region's culture of open information exchange and inter-firm mobility, which foster recombination and new firm formation." (Saxenian, p. 145, 2000)

4 "This freedom to experiment with product design is what distinguishes modular suppliers from ordinary subcontractors. For example, a team of disk drive designers has to obey the overall requirements of a personal computer, such as the data transmission protocols, specifications for the size and shape of hardware, and standards for interfaces, to be sure that the modules will function within the system as a whole. But otherwise, team members can design the disk drive in the way they think works best. The decisions they make need not be communicated to designers of other modules or even to the system's architects….Rival disk drive engineers, by the same token, can experiment with completely different engineering approaches for their versions of the module…"(Baldwin and Clark, 1997 p. 85)

5 Baldwin and Clark (1997, 2000) offer an extensive history and analysis of the central role that the development of modular design has played in the computer industry since the introduction of the IBM/360 in the 1960s. They define modularity as the "building of a complex product or process from smaller subsystems that can be designed independently yet function together as a whole" (Baldwin and Clark, 1997, p. 84).

These two features of Silicon Valley (multiple suppliers competing to produce innovative modular components and spillover of tacit knowledge via rapid employee mobility) meant that any firm connected to the personal networks through which information and employees flowed in Silicon Valley could benefit from the best innovation produced in the entire cluster rather than the best innovation produced by their own, proprietary research and development efforts.[6]

In support of her argument, Saxenien observed that the computer makers in the computer systems cluster around Boston organized their supply networks differently – and that this difference slowed the rate of innovation relative to Silicon Valley. Companies along Rte. 128 in Massachusetts (such as Digital Equipment Corporation) emphasized vertical integration and proprietary operating systems. The flow of information and ideas to competitors was further restricted by internal labor markets, compensation systems and informal employment practices that discouraged the easy movement of employees from one company to another. As a result of these differences, Rte. 128's computer makers lost the initial technological advantage they enjoyed over their competitors in Silicon Valley.

The key agglomeration economy in Saxenian's analysis was not the concentration of skilled employees in a region (Rte. 128 had a similar concentration), but the knowledge spillovers enabled by the easy mobility between firms.

> "This decentralized and fluid environment accelerated the diffusion of technological capabilities and know-how within the region. Departing employees were typically required to sign nondisclosure statements that prevented them from revealing company secrets: however much of the useful technology in the industry grew out of the

---

[6] "Why, asks Sun's vice president of manufacturing, Jim Bean, should Sun vertically integrate when hundreds of specialty shops in Silicon Valley invest heavily in staying at the leading edge in the design and manufacture of microprocessors, disk drives, printed-circuit boards, and most other computer components and subsystems? Relying on outside suppliers reduces Sun's overhead and ensures that the firm's workstations use state-of-the art technology "(Saxenian, 2000, p. 144)

> experience of developing technology. When engineers moved between companies, they took with them the knowledge, skills, and experience acquired at their previous jobs. (Saxenian, 1994, p. 37)

The phenomenon of knowledge spillovers enabled by job hopping between companies raises an important theoretical and managerial issue: if the tacit knowledge of departing employees includes new innovations developed by or at their current employer, why should the employer make it easy for employees to move? Wouldn't individual companies do better by taking advantage of the free flow of ideas from other firms in the Valley while locking up their own ideas and employees? Of course, if it makes sense for each individual firm to inhibit the movement of their ideas and their employees, the external economies of scale in Silicon Valley would rapidly disappear. How is it possible then that external economies of the sort described by Saxenian are an equilibrium feature of the equilibrium industrial cluster in Silicon Valley?

Ronald Gilson proposed a provocative answer to this question (1999). Gilson's analysis focuses on the legal mechanisms available to firms wishing to control the disposition of knowledge and ideas that employees acquire in the course of their work. As the preceding quote suggests, laws regulating the disclosure of trade secrets were not an effective device for controlling unwanted knowledge transfers. Indeed, according to Gilson, given the tacit nature of the knowledge spillovers in the Silicon Valley environment, the only potentially effective legal device for restricting the flow of important innovations to competitors would be a non-compete agreement.[7] These employment agreements limit an employee's ability to find work with

---

[7] Gilson (1998) argues that the two other legal approaches to controlling knowledge spillovers are largely ineffective in this context. Trade secrets law is of limited use because it is hard to differentiate tacit knowledge embedded in an employees human capital from a trade secret. Under the law governing invention, ideas remain an employee's property until the innovation is conceived, i.e. when the design of the invention is complete in the mind of the inventor. The

competitors located in a specified geographic area and for a specified period of time. It turns out that features of California state law introduced serendipitously in the 1870's, make it impossible for employers to enforce non-compete agreements. But for this historical accident, Silicon Valley employers would have had at their disposal an easy way of effectively eliminating knowledge spillovers of the sort documented in Saxenian's qualitative study. Since California's legal system is exceptional in its treatment of non-compete agreements, Gilson's story explains how the hyper-mobility described by Saxenian can be an equilibrium – employers simply couldn't establish effective control over tacit knowledge acquired by employees -- and it also explains why similar systems didn't develop in Route 128 and elsewhere where non-compete agreements were more easily enforceable.

Saxenian's and Gilson's accounts have captured much attention in management and policy circles. Their accounts are interesting for economic theory because they describe a setting where strengthening intellectual property rights via non-compete agreements can lead to a *reduction* in innovative activity. Unfortunately data limitations have, until now, precluded direct empirical examination of the key features of the story – especially the movement of employees between firms within a narrow geographic region and industry. In this paper we use set of questions in the *Current Population Survey* to assess the rate of employer to employer mobility in Silicon Valley and elsewhere.[8] Using this data we find strong evidence that employees working in the computer industry cluster in Silicon Valley do indeed have higher rates of

---

difficulty of establishing with objective evidence when this occurred makes invention law an ineffective means of regulating tacit knowledge spillovers.

[8] The only other paper we know of that examines mobility in high technology clusters is Almeida and Kogut (1999). They use patent records to study the mobility patterns of 438 individuals who held major, semiconductor-related patents. They find higher rates of mobility in Northern California than elsewhere in the country.

mobility than similar computer industry employees in other metropolitan areas having large information technology clusters. Second, and consistent with Gilson's hypothesis that California state law is the key feature sustaining hyper-mobile employment, there appears to be a "California" effect on mobility. That is we find similar high rates of mobility of computer industry employees throughout the state of California. Third, we find that the mobility patterns observed for employees working in the computer industry do *not* hold for employees in other industries residing in these same locations. This last result suggests that our findings are driven by features of the computer industry in a particular geographic location rather than features of the geographic area itself .

Our paper proceeds in three parts. In the next section we lay out a simple, model of the distinctive innovation process in computers. Using this model we find that the combination of modular components and tacit knowledge transfer is likely to produce a Silicon Valley type industrial structure and hyper-mobile employment only in a special set of circumstances. Specifically when the technological potential of component innovations is high but the best way to proceed is uncertain. In such a setting, increasing the number of competing suppliers simultaneously experimenting with innovative components, greatly increases the rate at which new technology is built into components.[9] Our model also finds that the greater the advantages to this type of innovation, the greater the steady state rate of employee turnover in the industrial cluster. Even under these conditions, however, we demonstrate that the Silicon Valley system would not be an equilibrium if employers could disrupt knowledge spillovers by limiting the

---

[9] Baldwin and Clark (1994, 2000) and Aoki (2001) observe that these conditions hold in the computer industry. "For an industry like computers, in which technological uncertainty is high and the best way to proceed is often unknown, the more experiments and the more flexibility each designer has to develop and test the experimental modules, the faster the industry is able to arrive at improved versions" (Baldwin and Clark, 1994, p. 85)

movement of employees from firm to firm. In section three, we present our empirical results. The paper concludes with a brief discussion of issues for further research.

A Model of Inter-firm Mobility and Innovation

In this section we present a simple model of innovation and mobility in an industrial cluster. We develop this model to demonstrate that the combination of tacit knowledge spillovers and modular components will produce a Silicon Valley type industrial organization and hyper mobile employment only under special economic conditions. We highlight two of these. The first is that the payoff to having the non-exclusive access to the "best" performing component in a product is far greater than the payoff to having exclusive access to an "average" performing component in the product. Second, for inter-firm mobility to be the primary mechanism of knowledge spillover, there must be some mechanism that prevents employers from "locking in" knowledgeable employees.

Our model posits an industrial district with two types of firms: suppliers and computer system manufacturers. The suppliers (represented by *S*) specialize in rapidly incorporating the latest technological innovations into the components of a computer system. The computer manufacturers (represented by *E*) purchase components and incorporate them into products that are then sold to business or individual consumers. To simplify the math and highlight the key relationships, we assume that all computer makers purchase a single component from suppliers. We further assume that computer manufacturers produce a similar product, such as a work station or server, but that each firm's product is differentiated in the sense that each commands a certain degree of brand loyalty from customers.

Innovation in Industrial Clusters

A fundamental feature of Silicon Valley's innovation system is that multiple suppliers simultaneously work on designing new components and computer makers select for their final product the component that proves to offer the best performance (Aoki, 2001, p. 353). This process of innovation, however, is inherently uncertain in that no one knows ex-ante which supplier will prove to have the best component ex-post.[10] A convenient way to model this uncertainty is to assume that the value of any supplier's innovation is determined by a random draw from a uniform distribution ranging between 0 and γ, where γ is the maximum feasible technical value of an innovation in components. In this case, the expected technical value of the "best" innovation produced by the S suppliers in the cluster is determined by the first-order statistic of the uniform distribution:

$$(1) \qquad \gamma \frac{S}{1+S} \text{ with } \gamma > 0$$

The important point to take away from (1) is that the expected value of the "best" innovation produced by the suppliers in a cluster increases with the number of suppliers in the cluster, although the marginal contribution of each new supplier declines as more of them enter the district.

In Saxenian's account, the primary advantage to a computer maker of locating in the Silicon Valley industrial cluster is that the company gains privileged access to the "best" component produced by the suppliers in the cluster. By being physically present in the Valley,

---

[10] Aoki's discussion of Silicon Valley emphasizes that much new innovation is undertaken by start-up firms backed by venture capitalists. The failure rate is high among these entrepreneurial ventures. "In casual conversations in Silicon Valley, venture capitalists normally regard three successes out of ten initial fundings as successful and two successes as acceptable." (Aoki, 2001, p. 373)

employees and employers can partake in the rich informal communication networks through which important knowledge and innovations diffuse. Vertically integrated computer makers located outside the district do not rely on suppliers of modular components. Rather, these manufacturers tend to design modules that are highly interdependent and they are therefore locked into whatever ex-ante design decisions their R&D departments make.[11] Maintaining our assumption that the technical quality of an innovation is determined by a random draw from a uniform distribution between 0 and γ, a vertically integrated computer maker can expect the quality of their in-house component to be 0.5γ.

In an environment like the computer industry, in which technological potential is high, but in which there is also uncertainty about how to realize that potential, we might expect there to be a heightened economic return from having numerous competing suppliers working to develop new components. Formally we write the difference in the performance of computers with the "best" components produced by a cluster relative to the expected performance of in-house components as: [12]

---

[11] The preference for interdependent components over modular ones is due in part to the fact that modular systems are more difficult and costly to design (Baldwin and Clark, 2000)

[12] One might wonder why, if experimentation is valuable, individual firms don't undertake simultaneous experiments using their own design teams, rather than relying on component suppliers. There are two explanations in the literature for why this may not take place. First, component suppliers often have advantages due to their greater specialization in the technology of components. Secondly, even if there were no gains from specialization, a rational computer maker would not undertake enough experiments to discourage outside suppliers from undertaking their own. This follows because in the "winner-take-all" supply network we model, each new component manufacturer entering the tournament reduces the odds that others will win. The computer manufacturer would take this externality into account when deciding on the number of design teams to set up, but independent suppliers would not. This point is made with respect to the difficulty IBM had in discouraging rival computer component suppliers for the IBM 360 in Baldwin and Clark (2000). The general point about the externalities generated by 'winner take all' markets is found in Frank and Cooke (1996).

(2) $\Omega = \gamma \frac{S}{1+S} - \frac{\gamma}{2}$

Notice that as long as S > 1, increases in γ, i.e. increases in the potential economic value of innovative new components, increase the performance premium associated with using the "best" components produced by competing suppliers. On this basis we would *not* expect Silicon Valley type supply clusters to evolve in industries where γ is small. We establish this point more precisely in the model that follows.

The Product Cycle for Computer Makers:

We posit that computer makers have a product cycle that begins in period *t* and lasts through period *t*+1 (see Figure 1 for a diagram outlining the timing of the model). At the beginning of period t, the manufacturer decides on the technology it will use over the next two periods and, having made this decision, purchases a component from a supplier that was developed in period *t*-1. Each computer maker purchases only one component and this component incorporates the best technology available in period *t*-1. Having made design and component purchase decisions, the computer maker is locked into its technology for the rest of the two period product cycle.

At the beginning of period *t* computer makers hire a fixed number of employees, β, out of college. We assume these employees have a work life of 2 periods, so they retire after period *t*+1. The prevailing wage for employees with the requisite education and skill is $\overline{w}$. Each computer manufacturer's product is differentiated, and they cannot therefore rely solely on the general technical knowledge employees may have acquired in college. Rather, they must also make substantial investments in firm-specific human capital prior to production in time t. This means that employee turnover is costly to the computer makers. We assume that employees stay with a computer maker unless they are hired away by suppliers. More on this in the next section.

We make two ancillary assumptions about timing to simplify the exposition and the mathematics. First computer manufacturers always survive through their product cycle. This means that computer makers present in period *t* can only exit the industrial cluster after period *t*+1. Second innovations built into components in period *t*-1 matter only for the product cycle beginning in period t. In product cycles beginning after period t, the technology would have changed enough that the components used in period *t* are useless. In other words, the value of technology embodied in components completely depreciates during the computer maker's product cycle. This assumption is consistent with the very rapid pace of technological change in the industrial districts described by Saxenian and many others.

The Product Cycle for Suppliers:

Suppliers who wish to sell components to computer makers need to develop their product prior to the start of the computer maker's product cycle. Thus a component incorporated into a product cycle beginning in period *t* must be developed in period *t*-1. We assume that it takes suppliers one period to develop the next generation version of the component they will sell to computer makers. This short product cycle, which is half that of the computer makers in our model, captures the rapid rate of innovation in Silicon Valley supply networks. Knowledge spillovers are required to produce a useful component. We capture this feature of the cluster by assuming that every supplier must hire one experienced employee from a computer maker. Following Saxenian, we assume that this inter-firm mobility is facilitated by geographically specific personal networks so that supplier firms hire only experienced engineers already at work in computer makers located in the district.

Since a component must be developed in period *t*-1 to be incorporated into a computer maker's product cycle in period t, it follows that suppliers wishing to sell components at the *end*

of period t-1, must hire an experienced employee from a computer maker at the *beginning* of period t-1.

Innovation in The Industrial District:

Location in the industrial district offers both benefits and costs to innovation. The benefit to computer makers from locating in the cluster is privileged access to the "best" innovation produced by component suppliers in the cluster.[13] The cost to locating in the industrial district is that all computer makers in the cluster will have access to the same innovative component technology. Since the computer makers in the cluster produce competing products, the value of access to these innovations decreases as the number of other computer makers in the district increases.[14]

We capture these innovation costs and benefits in the following payoff function:

$$\Pi_t^E = \tau \frac{\gamma S_{t-1}}{(1+S_{t-1})gE_t}\left(1+\frac{1}{1+r}\right) \text{ with } 0<\tau<1 \text{ and } g>0.$$

The expression $\gamma S/(1+S)$ is the expected value of a computer system that incorporates the "best" component produced by the S suppliers in the district. The parameter g captures the cost of having to "share" the best component technology with other computer makers in the district. It is perhaps useful to think of g as reflecting the degree of product differentiation in the market for computers. We divide the expected value of the computer system with the "best" component by g times the number of computer makers in the district to represent the loss to the firm when E_t

---

13 Location in the cluster allows for access to the cluster's best components because knowledge of these is disseminated through the personal networks in the cluster.

14 This is not to say, of course, that the value to consumers of these innovations in components is declining, only that when more firms have access to the technology it is harder for computer makers to capture this value.

competitors also offer products using the same component technology in period t. Parameter τ is the fraction of value created in each period by the component that accrues to the computer maker (the remainder, $1-\tau$, is paid to the suppliers), and r is the interest rate.[15]

The Market for Tacit Knowledge

We introduce tacit knowledge into our model by assuming that each start-up makes an offer to one and only one experienced employee working at a computer maker. The expected number of employees lost to suppliers is S_{t+1}/E_t. Since each of the computer makers has β experienced employees at the end of period t , the probability an employee at a computer maker will receive an outside offer at the end of period t is $S_{t+1}/\beta E_t$.

We use the parameter k to denote the per employee cost of losing an experienced employee at the end of period t and replacing the lost employee in period t+1 with a similarly skilled employee from outside the cluster.[16] It follows from this that computer makers will pay no more than k to prevent the loss of an employee and that suppliers must pay a wage of $\overline{w}+k$ to hire experienced employees. If experienced employees can earn a premium of k dollars with probability $S_{t+1}/\beta E_t$ in period t+1, then the computer maker can lower the *first* period wage it

---

15 More precisely, parameter τ represents the fraction of the producer surplus that accrues to the computer maker. In a fuller account, we could solve parameter τ as being determined by a bargaining process between suppliers and computer makers.

16 Parameter k includes both the cost of lost specific human capital that the employee acquired in period t and the reduced productivity of the replacement hired in period t+1.

pays employees by $kS_{t+1}/\beta E_t(1+r)$. [17] In effect employees pay for the valuable tacit knowledge they acquire by accepting a low starting wage: $\overline{w} - kS_{t+1}/\beta E_t(1+r)$. [18]

Payoffs to Locating in the Cluster

Taken together, the payoff to a computer maker operating within the district is

$$\Pi_t^E = \tau \frac{\gamma S_{t-1}}{(1+S_{t-1})gE_t}\left(1+\frac{1}{1+r}\right) - k\frac{S_{t+1}}{E_t}\frac{1}{1+r} - \beta\left\{\overline{w}\left(1+\frac{1}{1+r}\right) - \frac{kS_{t+1}}{\beta E_t(1+r)}\right\}$$

where the second expression is the cost of labor turnover and the third expression (in braces) is the cost of labor. This can expression can in turn be simplified to

$$\text{(3)} \qquad \Pi_t^E = \tau \frac{\gamma S_{t-1}}{(1+S_{t-1})gE_t}\left(1+\frac{1}{1+r}\right) - \beta\left\{\overline{w}\left(1+\frac{1}{1+r}\right)\right\}.$$

Notice that the cost of employee turnover is "paid for" by the lower starting wage in period *t and* that the employees of the computer firm receive the same expected compensation over their two period work lives as they would elsewhere.

We now turn our attention to the payoff equation for suppliers. We assume that the suppliers present in the cluster at the beginning of each period are all equally likely to produce the "winning" innovation. Thus we can write expected payoff for suppliers at the beginning of period *t* as:

---

17 Moen (2000) presents evidence that employees in R&D intensive firms pay for the knowledge they accumulate on the job via lower wages in the beginning of their careers. The second period wage must be fixed at the prevailing market wage, $\overline{w}$, so as not to lose their remaining experienced employees.

18 Computer makers might also impose bonds on employees repayable after period t+1 to discourage mobility. These employment bonds are unlikely to be sufficient size to discourage all mobility (see Ritter and Taylor, 1994, for a discussion). Including the possibility of such bonds in our model would greatly increase its complexity without adding much insight.

$$\Pi_{t-1}^{S} = \frac{E_t}{S_{t-1}}\left\{\left[\frac{\gamma S_{t-1}}{(1+S_{t-1})gE_t}(1+\frac{1}{1+r})\right](1-\tau)\right\}-(\overline{w}+k) \tag{4}$$

$$= \frac{\gamma}{g(1+S_{t-1})}(1-\tau)\left(1+\frac{1}{1+r}\right)-(\overline{w}+k)$$

The expression in brackets is the expected value that the component produces for each computer maker over the course of the product cycle. The supplier receives (1-τ) of this value. Thus the expression in braces is the amount the "winning" supplier receives from each of the E_t computer makers who buy the component. Ex ante there are S_{t-1} suppliers who are equally likely to produce a winner. Thus E_t/ S_{t-1} times the expression in braces is the expected payoff for the suppliers in period *t*-1. The expression $(\overline{w}+k)$ is the cost of hiring an experienced employee from a computer maker in the cluster. Note that suppliers' expected payoff decreases in the number of suppliers in the industrial district.

Innovation and Turnover in The Steady State

From equations (3) and (4), it is clear that the number of computer makers and suppliers in the district has a direct influence on the payoffs from innovation in components. In this section, we use these equations to solve for the steady state composition of firms in the industrial district as well as the rate of turnover in the district.

To derive the steady state composition of the industrial district, we specify χ as the payoff on the best alternative use of suppliers' resources. When expected payoffs exceed χ , new suppliers enter the district. Conversely suppliers exit when expected payoffs fall below χ. Dropping the time subscripts, it follows from this assumption that the steady state condition for suppliers can be written:

$$(5) \qquad \chi = \frac{(1-\tau)\gamma}{g(1+S)}\left(1+\frac{1}{1+r}\right)-(\overline{w}+k) \Leftrightarrow S = \frac{(1-\tau)\gamma}{g(\chi+(\overline{w}+k))}\left(1+\frac{1}{1+r}\right)-1$$

The cluster only persists when there are positive values for E and S in the steady state. Positive values of S require γ large enough that $\frac{(1-\tau)\gamma}{g(\chi+(\overline{w}+k))}\left(1+\frac{1}{1+r}\right) > 1$.

For computer makers in the cluster, an intuitive alternative use of resources is to locate outside the cluster and produce the component themselves. Maintaining our assumptions regarding technological innovation and turnover, the vertically integrated computer maker outside the cluster would have an expected payoff of γ/2. The steady state condition is then:

$$(6) \qquad \begin{aligned} &\frac{\gamma}{2}\left(1+\frac{1}{1+r}\right)-\beta\overline{w}\left(1+\frac{1}{1+r}\right)=\frac{\tau\gamma S}{(1+S)gE}\left(1+\frac{1}{1+r}\right)-\beta\overline{w}\left(1+\frac{1}{1+r}\right) \Leftrightarrow \\ &E=\frac{\tau 2S}{g(1+S)} \end{aligned}$$

It is immediately clear from (6) that when S = 0, E = 0, computer makers will not enter a cluster if there are no suppliers there and vice versa.

Setting the discount rate equal to zero for algebraic convenience, the closed form solution for the number of each type of firm in the district is:[19]

$$(7) \quad E = \frac{\tau(2\gamma(1-\tau)-(\chi+(\overline{w}+k))g)}{\gamma g(1-\tau)}$$

$$(8) \quad S = \frac{2\gamma(1-\tau)-(\chi+(\overline{w}+k))g}{g(\chi+(\overline{w}+k))}$$

---

[19] The district will have positive numbers of suppliers and computer makers so long as $2\gamma(1-\tau)-(\chi+(\overline{w}+k)g) > 0$.

It is clear from inspection that the industrial cluster will exist (i.e. there will be positive steady state numbers of computer makers and suppliers) only when γ is sufficiently large that the numerators in (7) and (8) are positive. It is also clear that both $dE/d\gamma$ and $dS/d\gamma$ are positive.

In our stylized labor market, each of the β employees hired by the computer makers stay with the company for their entire two period work life unless they are recruited by suppliers at the end of period 1. Under the assumption that suppliers recruit employees at random, the steady state number of employees leaving each computer marker for other jobs in the cluster is:

$$(9)\ \frac{S}{E} = \frac{(1-\tau)\gamma}{\tau(\chi + (\bar{w} + k))}$$

The larger the number of suppliers relative to computer makers, the greater the turnover rate in the industrial cluster. Thus, so long as the parameters are such that the cluster exists, increases in γ produces both a larger cluster and one with more turnover.[20]

Inter-firm Mobility as the Mechanism for Knowledge Spillovers:

Each computer maker in the district could increase payoffs if it could find a way to prevent the loss of experienced employee talent to suppliers. In terms of our payoff function in equation (3) above, each computer maker will be better off if it can reduce its turnover rate, S/E. From this it follows that either: (1) the Silicon Valley model developed so far is not an equilibrium phenomenon or (2) that firms do not have the ability to restrict the mobility of critical employees. Gilson (1999) argues in favor of this second explanation. Specifically he claims that the legal instruments that can effectively inhibit the loss of employees with important

[20] In this model, all job-hopping is from computer makers to suppliers. We could extend the model to include job-hopping between computer makers or between suppliers too. Introducing these additional flows would complicate the algebra without altering our key results.

tacit knowledge, i.e. non-compete agreements, are not legally enforceable in California. They are, however, enforceable in most other states.[21] From this it follows that the high rates of inter-firm mobility in information technology clusters should be different in California than in other states.

We can make this argument more formally by assuming that where employers have the opportunity to exercise non-compete agreements, the suppliers can successfully recruit experienced employees from the computer industry only a fraction, θ, of the times they make offers. As a result of this only a fraction, θ, of the suppliers that make offers to experienced employees will be able to form. Adding these assumptions into our model, we get the resulting closed form solution for S/E [22]:

$$\text{(10)} \qquad \frac{S}{E} = \frac{\theta(1-\tau)\gamma}{\tau(\chi + (\overline{w} + k))}$$

It is immediately clear that the derivative of *S*/*E* with respect to θ is positive. Thus as the ability of non-compete agreements to impede mobility increases, i.e. as θ falls, the ratio of suppliers to computer (*S/E)* and the steady state number of employees job-hopping from a computer maker to suppliers, $\theta(S/E)$, also falls. Thus, to the extent that non-compete agreements restrict the ability of suppliers to recruit experienced employees; the turnover in the industrial district should also fall. It is similarly easy to show that d*S*/dθ < 0. Since the expected value of innovation in the

---

[21] Colorado is an exception, as we discuss in footnote 31 below.

[22] In this case we rewrite our stead state conditions as

$$\frac{\gamma}{2} - \beta\left\{\overline{w}\left(1+\frac{1}{1+r}\right)\right\} = \tau\frac{\gamma S_{t-1}}{(1+S_{t-1})gE_t}\left(1+\frac{1}{1+r}\right) - \beta\left\{\overline{w}\left(1+\frac{1}{1+r}\right)\right\} \text{ and}$$

$$\chi = \theta\left[\frac{\gamma}{g(1+S_{t-1})}(1-\tau)\left(1+\frac{1}{1+r}\right) - (\overline{w}+k)\right]$$

It follows from the second of these conditions implies that *d*S/*d*θ< 0

district increases with the number of suppliers, it follows that the rate of innovation in the cluster *falls* as intellectual property rights enforced through non-compete agreements increases.

Empirical Results

In this section we use new data on employee mobility to answer two questions that follow directly from Saxenian's and Gilson's discussions of agglomeration economies in Silicon Valley. First, is the inter-firm mobility of employees in the computer industry higher in Silicon Valley than in other IT clusters elsewhere? Second, is there a "California" effect on the rate of inter-firm mobility for computer industry employees?

The model in the preceding section makes clear that the hyper-mobility of employees in industrial clusters is likely to apply in only a limited set of circumstances. This insight leads us to consider a third empirical question: do the mobility patterns we observe in the computer industry hold for employees in the same location who are not employed in the computer industry?

Data:

The mobility data we need for our investigation must track the movement of employees from one firm to another within a given geographic location. In addition, the survey must be of sufficient size to study mobility in narrowly defined industries and geographic areas. These data were not in general use prior to the recent work by Fallick and Fleischman (2002) on employment flows. In their study they exploited changes in the structure of the Current Population Survey (CPS) 1994 to gain new information on employee mobility.

With the redesign of the CPS in January 1994, the Census Bureau ended its practice of asking all respondents every question afresh in each month. To avoid unnecessary duplication, interviewers asked some questions that refer back to the answers given in the previous month.

One specific instance of this new "dependent interviewing" approach allowed for the collection of the mobility data we use in this study. If a respondent is reported to be employed in one month and was also reported to be employed in the previous month's survey, the interviewer asks the respondent whether they currently work for the same employer as reported in the previous month (the interviewer reads out the employer's name from the previous month to ensure accuracy). If the answer is yes, then the interviewer carries forward the industry data from the previous month's survey; if the answer is no, then the respondent is asked the full series of industry, class, and occupation questions. Using the answer to this routing question, we can identify stayers (workers employed in two consecutive months at the same employer) and movers (workers who changed employers between two consecutive months).

For our purposes, this new CPS data is the best source of information on employer-to-employer mobility in the United States. The size and scope of the CPS sample is far greater than in most other household-based survey data and this allows for quite detailed analysis by geographic location, educational level, and industry. In addition, the CPS survey is administered monthly and this should reduce the recall errors found in other household surveys that ask respondents to remember over the previous year. Finally, we can link the employment transition data to demographic and employment data for each individual. This allows us to consider the importance of potentially confounding influences on employer to employer mobility.

The phenomenon we seek to study, the role of employer to employer mobility in facilitating knowledge transfer in the computer industry, is most relevant for highly educated employees. For this reason, we restrict our sample to those having a minimum of four years of

college who also live in metropolitan areas having information technology clusters.[23] In addition, we focus our analysis on men to eliminate the potentially confounding effect of gender on mobility. Finally, we pool across all the years for which employer-to-employer data is available, 1994 – 2001 in order to achieve a sample in the computer industry large enough for analysis. All of our results include fixed year and month-of-interview effects to net out the influence of year to year as well as seasonal variation in economic activity. The resulting sample has 44, 202 individuals and 156,149 month-to-month observations. The number of month to month observations observed for each individual ranges from 1 to 6 with the median being 3.[24] Of the individuals in our sample, 3,768 (or 7.84%) were observed to have changed employers at least once. The monthly rate of employer to employer job change is 2.41 percent. [25]

---

23 Information on metropolitan areas with the top 20 IT clusters by employment in the year 2000 is taken from The Cluster Mapping Project (2003). We include the following metropolitan areas (MSAs): San Jose; Boston (with Worcester Lawrence MA_NH); Austin; Dallas; Seattle; Phoenix; Orange County; Washington; Portland; San Francisco; Raleigh; Chicago; Los Angeles; San Diego; Minneapolis; Oakland; Atlanta; Phil.; Houston; and Denver. Details on the identification of clusters are in Porter (2003).

24 The CPS has a short panel structure – respondents are in the sample for four consecutive months, out for 8 consecutive months and in again for four consecutive months. This means that for each individual we can observe at most 6 month-to-month potential transitions. The median is less than 6 for the following reasons: (1) some individuals final four months occurred in 1994; (2) some individuals' final four months occurred in 2001; and (3) for administrative reasons only 6 months of data were collected in 1995. In addition, some individuals move from one month to the next and these are lost to the survey because an individual is identified, in part, by the location of their residence. After taking account of factors (1)-(3) above, the number of individuals lost due to change of address or data errors is consistent with other published studies. Details on the matching algorithm we used to match individuals from one month to the next are available in Fallick and Fleishman (2002).

25 To put this figure in perspective, if we assume this rate of mobility holds for every month an individual is on a job, then the probability a newly hired employee will be at the job in one year is $(1-.0241)^{11} = 0.76$. Of course the hazard of exiting a firm is not constant and the rate of mobility is likely to vary a great deal depending on many factors including age and tenure on the job.

Results:

Our empirical investigation requires that we identify employees in the computer industry. If we define this industry too broadly, we risk including in our sample employees who are not part of the computer cluster. Alternatively a very narrow definition risks excluding some employees who ought to be counted as part of the cluster. For this reason, we present our key results in Tale 1 and 2 using both a broad and narrow definition of the industry.

Table 1 estimates rely on a broad definition of the industry. In it we present probit estimates of the probability that an individual in SIC 35 and 36 in month *t* changes employers before being re-interviewed in month *t* +1. [26] The estimates in column 1 and 2 are for a sample of 2972 men having 8966 month-to-month observations. The mean of the dependent variable is 0.0195 suggesting that employers were observed to change employers in 1.95 percent of the potential transitions. All the probit estimates are presented as derivatives evaluated at the mean of the right-hand side variable for continuous variables and between 0 and 1 for dummy variables. Thus the 0.012 coefficient for the variable *San Jose* in column 1 indicates that living in Silicon Valley increases the rate of employer to employer job change by 1.2 percentage points. This effect is both statistically and behaviorally significant -- suggesting employer to employer mobility rates are more than 60% higher the sample average. On this basis, the hyper-mobility that Saxenian observed in her ethnographic studies of the late 80's and early 90's appears to persist in Silicon Valley throughout the 1990's.

---

[26] SIC 35 and 36 constitute a conventional but overly broad definition of the computer industry as can be seen by the titles of these SICs: Industrial and Commercial Machinery and Computer Equipment; and Electronic and Other Electrical Equipment and Components, Except Computer Equipment. We present results for a more narrow definition in Table 2.

Column 2 of Table 1 introduces a new variable, *California*, which is a dummy variable equal to 1 if an employee in the computer industry in time *t* resides in a metropolitan area with an IT cluster in the state of California. In this specification, we observe that the coefficient on *San Jose* falls dramatically in magnitude and becomes statistically insignificant while the coefficient on *California* is both behaviorally and statistically significant. Ceteris paribus, employees in California's IT industries have a rate of employer to employer mobility that is 0.9 percentage point above the sample mean (z score 2.40) – an increase of 46 percent. These results are consistent with Gilson's hypothesis regarding California law, the Silicon Valley effect on mobility appears to run throughout the state.

Column 3 of Table 1 estimates job change rates separately for each of the MSAs in California having IT clusters. In addition, we find that the *California* effect is not due solely to MSA's that abut *San Jose.* While residing in *San Jose* increases mobility in computer firms by 1.5 percentage points, *San Francisco* residents have mobility rates 0.2 percentage points above the national average and the standard errors on this estimate are very large. In contrast, residents of *Los Angeles* and *San Diego* had mobility rates virtually identical to *San Jose.* The coefficient on *Los Angeles* is statistically significant at the 5% level and *San Diego* is significant at the 10 percent level. This reinforces the conclusions drawn from column 2, i.e. that the high Silicon Valley mobility rates can be found elsewhere in California.[27]

The mobility measures used in columns (1) through (3) look at all job changes for employees in the computer industry in month *t* regardless of the industry to which they move. In contrast the estimates columns (4) through (6) count as moves only those job changes in which the employer in month *t* and in month *t*+1 are in the computer industry. The mean of this

---

[27] Of the 886 individuals in our sample who lived in California, 342 (under 40%) live in San Jose.

new intra-industry measure of job change is 0.009, indicating that roughly 46% of the employer to employer job changes for employees in the computer industry are to other employers in the same two SIC industries.

The results in column (4) confirm the presence of high rates of employer to employer mobility in Silicon Valley. The coefficient on *San Jose* is 0.009 (z score = 3.10), suggesting that this measure of job change is 50% higher in San Jose than the sample mean. Column (5) introduces a California dummy. This coefficient on this new variable is positive, but small in magnitude (0.003) and imprecisely measured (z = 1.36). As importantly the coefficient on *San Jose* falls by a third and also becomes statistically insignificant at conventional levels. One can, however, easily reject the hypothesis that *San Jose* and *California* are jointly insignificant (chi2(2) = 11.28 and Prob > chi2 = 0.0035). Taken together, these results suggest that given the smaller number of employer to employer moves within the computer industry (narrowly defined), it is difficult to distinguish reliably a San Jose effect from a California effect.

In column (6) we disaggregate the California effect by looking at individual MSAs. We observe a very large and positive coefficient on *San Jose* (0.01 significant at the 1% level). We also find that the coefficient on *San Francisco* is even larger and nearly statistically significant at the 10% level (0.012 with a *z*-statistic of 1.89). In contrast the coefficients on the other California MSA's are essentially zero and very imprecisely measured.

Taken together, the results in column (6) support Saxenian's claim that intra-industry mobility is higher in *San Jose* than in computer industries located elsewhere. These results do not offer support for Gilson's hypothesis -- heightened mobility seems to be concentrated in *San Jose* and nearby *San Francisco*, but is not observed in other MSAs.

Why do we observe a *California* effect on mobility in columns (1)-(3), but not in columns (4)-(6)? The answer can be found in the different mobility measures we employ. The intra-industry measure of mobility used in (4)-(6) is the right measure to the extent that the boundary of the cluster corresponds to SIC industry classifications. If, however, the boundaries of the cluster are not identical to the definition of the SIC industries, the measure in column (1)-(3) that counts all job changes for employees initially in SIC 35 and 36, might give a more accurate picture of mobility rates. To see this consider what would happen if all jobs in SIC 35 and 36 are in the IT cluster, but that the cluster also bleeds over into other related industries. For concreteness, imagine that the rate of job hopping in San Jose and Los Angeles' IT clusters were identical but 100% of the employees in San Jose's cluster are in SIC 35 and 36 while in Los Angeles, only 50% of the employers in the IT cluster located in SIC 35 and 36. Perhaps the remaining 50% are located in industries that make instruments used in computers and are therefore classified in SIC 38. Using the measure of mobility in columns (1)-(3) (that counts all mobility in jobs that originate in SIC 35 and 36) we would find that job hopping rates are the same in Los Angeles and San Jose, but using the alternative measure (that accounts only job changes within SIC 35 and 36) the measured rate of job change would be higher in San Jose than LA. There is some reason to believe that the boundaries of IT clusters do bleed into other industries and that this varies systematically by city.[28] For this reason we interpret the absence of a *California* effect in columns (4)-(6) with some caution.

---

[28] In a private communication concerning an early draft of this paper, Saxenian observed that the computer clusters in Silicon Valley and San Francisco are highly concentrated in firms that belong in SIC 35 and 36, while the LA/Orange County/San Diego clusters tend to bleed into other industries – especially instrumentation.

Columns (7) and (8) compare the "California" effect on mobility to the "Massachusetts" effect for each of our measures of employer to employer changes.[29] Massachusetts is interesting because it has the second largest IT cluster after Silicon Valley as well as a very different set of legal rules governing non-compete agreements. In both equations we find a large, and statistically significant coefficient on *California*. We also observe that the coefficient on *Massachusetts* is smaller than that on *California*, and that the difference is large in column (7) and small in column (8). Indeed both columns, however, the *Massachusetts* coefficient is imprecisely measure and one cannot reject the hypothesis that it is zero at conventional significance levels. Unfortunately this imprecision in measurement also means that we cannot reject the hypothesis that the coefficient on *California* is the same as the coefficient on *Massachusetts*.[30] Our conservative conclusion is that if a *Massachusetts* effect exists at all, we cannot be sure that it is different than the *California* effect.[31]

The results in Table 1 are based on a very broad definition of the computer industry, employees working in establishments that fall into SIC industries 35 and 36. In Table 2, we redo

---

29 Our sample is confined to respondents in MSA's defined by Porter as having an information technology cluster. Thus all the respondents for which *Massachusetts* is equal to one are in MSA 1120.

30 A χ^2 test of the hypothesis that *California* = *Massachusetts* in column (7) yields: χ^2 (1) = 0.50 Prob > χ^2 = 0.4799. The similar test for equation (8) yields χ^2 (1) = 0.32 Prob > χ^2 = 0.5699

31 Colorado is similar to California in that its state law prohibits non-compete agreements. There are, however, a number of exemptions to this law. For our purposes the most important one is that non-compete's are allowed if they are intended to protect trade secrets. Inserting a dummy variable for Denver into our Table 1 regressions one finds that working in Denver's computer industry increases the probability of job change by 2 percentage points but the estimate is quite imprecise (z = 1.42). It is hard to know if this imprecision is due to the importance of the loophole in the Colorado law or to the small number of observations in Denver, the only MSA in Colorado with an IT cluster.

the analysis using a more narrow definition.[32] The results are qualitatively and quantitatively close to those in Table 1. We conclude from this that our findings are not likely to be an artifact generated by the way we define the computer industry.

Our model of innovation in industrial clusters suggests that hyper-mobility ought *not* to be a general feature of Silicon Valley or California labor markets. Indeed, if we found evidence of hyper-mobility outside of computers, we might worry that the effects we are attributing to the industrial organization of IT clusters may be due to other, unobserved and unexplored, aspects of these labor markets. In Table 3, we examine mobility patterns for employees not employed in the computer industry in month *t*. We restrict the sample to employees not employed in SIC 35 or SIC 36 in month *t*. Our dependent variable is equal to 1 if an employee changed employers before the interview in month *t*+1. Comparing the average monthly job change rates conditional on being employed in the computer industry (0.0195) with the average conditional on not being employed in the computer industry (0.0244), it appears that employer to employer movements are more common outside SIC 35 and 36

In column 1 of Table 3, the coefficient on *San Jose* is small (about 1/10th of the mean mobility rate of the population) and we cannot reject the hypothesis that the true effect is zero. Columns 2 and 3 introduce a California dummy variable into the equation. The coefficient on *California* is also small and negative and not precisely measured considering the very large sample size. A χ^2 test does not allow us to reject the hypothesis that *California* and *San Jose* are

---

[32] Specifically our narrow definition includes employees in two three-digit census industries: computers and related equipment (Census 322); and electrical machinery, equipment, and supplies, not elsewhere classified (Census 342). Census 322 includes: electronic computers (SIC 3571); computer storage devices (SIC 3572); computer terminals (SIC 3575); and computer peripheral equipment, not elsewhere classified (SIC 3577). Census 342 is a residual category from which most non-computing electrical devices has been excluded.

jointly insignificant in column 3.[33] Similarly when we introduce dummy variables for the California MSA's with IT clusters (see column 4), we find no evidence that outside the computer industry job changes are more likely within California. Indeed rates of job-hopping appear lower Los Angeles and San Diego than elsewhere in the nation. Taken together, these results in Columns 2 through 4 suggest that the high relative mobility rates in Silicon Valley and California do *not* hold outside of the computer industry.

We conclude our empirical analysis by considering an alternative explanation of our results that has to do with job search rather than the structure of innovation in computers. It is possible that mobility rates are higher in the computer industry in Silicon Valley because the high density of computer related employment creates a thick market for similarly skilled college educated men that makes it easy to find a good outside match. If this argument is correct, then looking outside of computers, one should find that a high density of information technology jobs or jobs for college educated men in their own industry ought also to be associated with high rates of job turnover. To assess this we introduce two measures of job density into the job change regressions. The first measure, *Location Quotient IT* , is a measure of the density of employment in the IT cluster in a respondent's MSA.[34] The second measure, *Location Quotient Own Industry*, estimates the density of employment in a respondent's industry and MSA relative to the national average.[35] Introducing these variables into a job change equation yields positive

---

33 $\chi^2(2) = 4.32$.

34 This variable is constructed by dividing the fraction of MSA employment in it's IT cluster by the national average of the fraction of IT employment in the year 2000. See Cluster Mapping Project (2003), for details. The average *Location Quotient IT Industry* > 1 in our sample because we limit our analysis to MSA's having IT clusters.

35 This variable is constructed from our sample of college educated men. For each individual, we calculate the fraction of employment in their two digit census industry in their MSA pooling across the years 1994-2001. We then divide this by the average of all MSA's in our sample.

coefficients that are very imprecisely measured considering the size of the sample. Thus we cannot reject the null hypothesis that either *Location Quotient IT* or *Location Quotient Own Industry* have zero effect on mobility. We also cannot reject the hypothesis that these coefficients are jointly insignificant.[36] On this basis it does not appear that our results can be explained simply by the thickness of the local market for college educated employees in their own industry or in IT industries.

Conclusion

This paper has compared the inter-firm mobility of highly educated employees in computer firms in Silicon Valley relative to similarly educated employees working in computer firms in information technology clusters located in other cities. Using a new data source, we find that there is substantially more job mobility in Silicon Valley than elsewhere, and that this differential disappears when we look outside the computer industry. These results are consistent with more qualitative descriptions of the way that ubiquitous knowledge spillovers in Silicon Valley are enabled by the rapid and easy movement of employees between firms.

In addition, we find that the hyper mobility of employees in computer firms in Silicon Valley can also be observed in IT clusters throughout California. The evidence for a California effect is weaker than for the Silicon Valley effect because it is sensitive to the mobility measure we employ. The existence of a California effect would be important because it is consistent with the idea, suggested by some legal scholars, that California state laws which make non-compete agreements all but unenforceable, are important for sustaining knowledge spillovers.

Thus when *Location Quotient Own Industry* = 1, the respondent's MSA has the same fraction of employment in an industry as does the average MSA.

36 χ^2 (2) = 2.89. We also find that these density measures have no influence on job changes if we insert them into the Table 1 equations that focus only on employees in the computer industry.

While our results lend support to some influential accounts of the success of Silicon Valley, it is important to emphasize the limitations of our study. Two caveats seem especially important. First, the new evidence we bring to light in this paper allows us to observe the movement of employees between firms in a geographic location – but not the actual knowledge handoffs that these movements are supposed to facilitate. Thus we cannot rule out the competing hypothesis that rapid employee mobility may be the result of some unobserved features of computer firms in California rather than the catalyst enabling superior information exchange. If, for example, Silicon Valley has many more start-up firms than other IT clusters and if start-ups simply churn through employees more rapidly than other firms, we would see more mobility, but not necessarily more knowledge spillovers, in Silicon Valley than elsewhere.[37]

Second, while there appears to be a "California" effect on mobility in information technology clusters, we have no direct evidence that this is due to the absence of enforceable non-compete agreements. As a result we cannot rule out the role that other factors (such as local culture) may play in sustaining high rates of employee turnover. [38]

Even with these limitations, we believe that the study of turnover in industrial clusters could shed some light on the general applicability of theories of agglomeration economies. Our theoretical analysis suggests Silicon Valley type industrial districts ought *not* to be a general economic phenomenon. Rather they should only arise in settings where the value of having non-exclusive access to the "best" (as opposed to exclusive access to the average) innovation is large.

---

[37] Of course "start-ups" are an organizational form particularly well suited to the modular supply networks and tacit knowledge spillovers highlighted by Saxenian (1994). Indeed the heightened inter-firm mobility of employees in start-ups can *itself* be an important mechanism for knowledge spillovers in Silicon Valley.

[38] Cultural factors are not, of course, mutually exclusive explanations of mobility. If culture plays a role in job-hopping in Silicon Valley it is easy to see how they could reinforce the factors we include in or model of mobility

Qualitative evidence collected by Saxenian, Baldwin and Clark and other observers suggests that this condition likely holds in the computer industry. Agglomeration economies may, of course, have sources other than knowledge spillovers facilitated via employee turnover. It would be useful to search for other industries and industrial clusters where this condition might hold to see if these locations are also characterized by enhanced inter-firm mobility.

References

1.) Almeida, Paul and Kogut, Bruce., (1999) "Localization of Knowledge and the Mobility of Engineers in Regional Networks" Management Science. 45:7. p. 905-917.

2.) Angel, David P., (1989) "The Labor Market for Engineers in the U.S. Semiconductor Industry" Economic Geography. 65:2. p.99-112.

3.) Aoki, Masahiko, (2001) Toward a Comparative Institutional Analysis. The MIT Press : Cambridge, Massachusetts and London, England.

4.) Baldwin, Carliss Y. and Clark, Kim B., (1997) "Managing in an Age of Modularity" Harvard Business Review. p.84-93.

5.) Baldwin, Carliss Y. and Clark, Kim B., (2000) Design Rules: The Power of Modularity. MIT Press : Cambridge, Mass. and London, England.

6.) Cluster Mapping Project (2003), Institute for Strategy and Competitiveness, Harvard Business School

7.) Fallick, Bruce C. and Fleischman, Charles A., (2002) ""Employer to Employer Flows in the U.S. Labor Market" Working Paper. April 2002.

8.) Frank, Robert H. and Cooke, Phillip. (1996) The Winner Take All Society. Penguin Publishers, United States.

9.) Gilson, Ronald, (1999) "The Legal Infrastructure of High Technology Industrial Districts: Silicon Valley, Route 128, and Covenants Not to Compete." New York University Law Review. 74:. p.575.

10.) Moen, Jarle, (2000) "Is Mobility of Technical Personnel A Source of R&D Spillovers?" National Bureau of Economic Rsearch. No.7834. August 2000.

11.) Porter, Michael E., (2003) "The Economic Performance of Regions" Regional Science. 37.:6&7. p.549-578.

12.) Porter, Michael E., (1998) "Clusters and The New Economics of Competition" Harvard Business Review. 76:6.

13.) Ritter, Joseph A; Taylor, Lowell J., (1994) "Workers as Creditors: Performance Bonds and Efficiency Wages" American Economic Review. 84:3. p.694-704.

14.) Rosenthal, Stuart S. and Strange, William C., (2003) "Evidence on the Nature and Sources of Agglomeration Economies" Working Paper Prepared for the Handbook of Urban and Regional Economics, vol. 4. February 9, 2003.

15.) Saxenian, Annalee, (1994) Regional Advantage: Culture and Competition in Silicon Valley and Route 128. Harvard University Press : Cambridge, Massachusetts and London England.

16.) Saxenian, Annalee, (1996) "Inside-Out: Regional Networks and Industrial Adaptation in Silicon Valley and Route 128" Cityscape. 2:2. p.41-60.

17.) Saxenian, Annalee, (2000) "The Origins and Dynamics of Production Networks in Silicon Valley" Understanding Silicon Valley: The Anatomy of an Entrepreneurial Region. edited by Martin Kenney. Stanford University Press :Stanford.

Figure 1

Timing of the Model

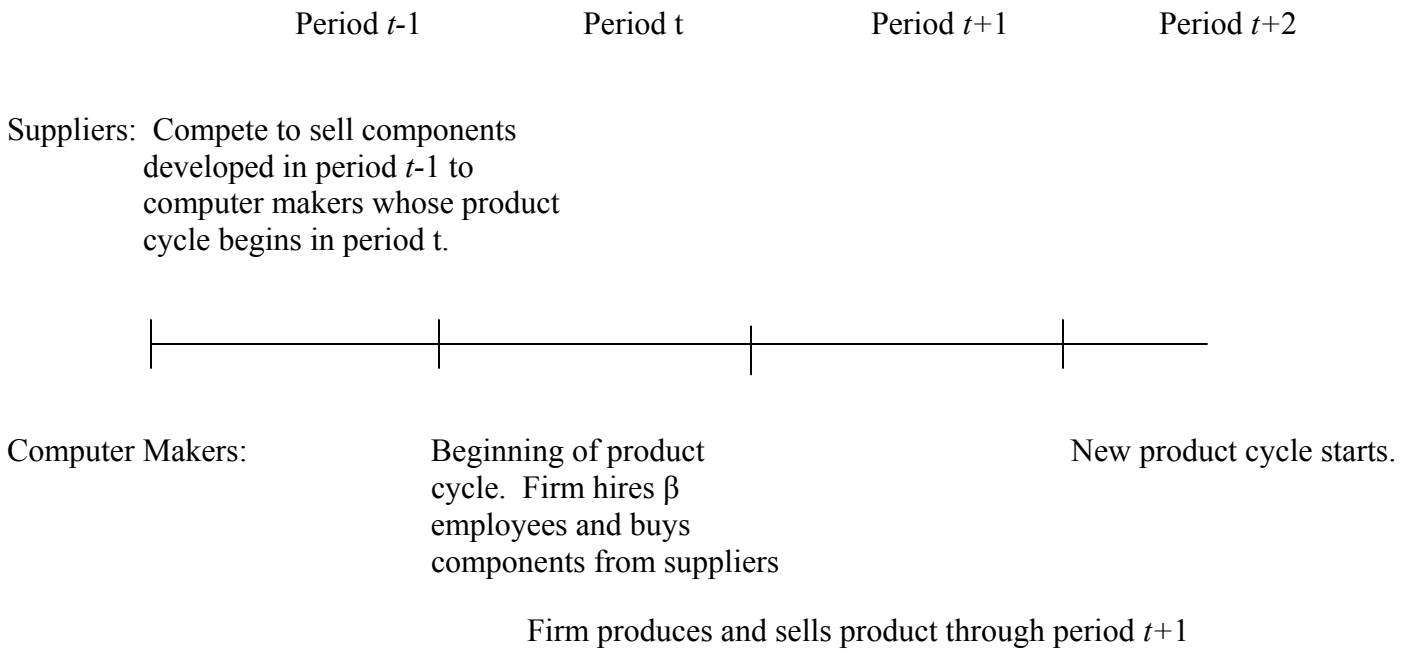

Table 1

Determinants of Month-to-Month Job Changes: Conditional on Being in The Computer Industry Broadly Defined (SIC 35 and 36)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable [mean]	Change Jobs [0.0195]	Change Jobs [0.0195]	Change Jobs [0.0281]	Change Jobs Within Industry [0.009]	Change Jobs Within Industry [0.009]	Change Jobs Within Industry [0.009]	Change Jobs [0.0195]	Change Jobs Within Industry [0.009]
San Jose [0.122]	0.012	0.004	0.015	0.009	0.006	0.01		
	(2.40)*	(0.80)	(2.87)**	(3.10)**	(1.77)	(3.31)**		
California [.302]		0.009			0.003		0.012	0.006
		(2.40)*			(1.36)		(3.43)	(2.98)
San Francisco [.017]			0.002			0.015		
			(0.23)			(1.89)		
Los Angeles [0.069]			0.015			0.004		
			(2.43)*			(1.05)		
Orange County [0.030]			0.002			0.000		
			(0.30)			(0.09)		
San Diego [0.037]			0.015			0.00		
			(1.88)			(0.41)		
Massachusetts [0.089]							0.008	0.005
							(1.48)	(1.24)
Full-Time [0.961]	0.002	0.002	0.002	0.005	0.005	0.005	0.002	0.005
	(0.34)	(0.34)	(0.34)	(1.24)	(1.23)	(1.25)	(0.35)	(1.23)
US Citizen [0.748]	-0.002	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.002
	(0.57)	(0.25)	(0.22)	(0.76)	(0.56)	(0.58)	(0.37)	(0.82)
Married [.753]	-0.003	-0.002	-0.002	0.000	0.000	0.000	-0.002	0.000
	(0.80)	(0.69)	(0.69)	(0.21)	(0.16)	(0.06)	(0.64)	(0.12)
Post College Schooling [.332]	0.001	0.001	0.001	-0.001	-0.001	-0.001	0.001	-0.001
	(0.33)	(0.42)	(0.47)	(0.50)	(0.45)	(0.53)	(0.36)	(0.42)
Year Fixed Effects 1994 - 2001	yes	yes	yes	yes	yes	yes	yes	yes
Month fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Age Dummy Variables	yes	yes	yes	yes	yes	yes	yes	yes
Observations	8966	8966	8966	8966	8966	8966	8966	8966
Number of Individuals	2972	2972	2972	2972	2972	2972	2972	2972

Absolute value of robust z-statistics in parentheses (with standard errors adjusted for clustering within individual). * significant at 5%; ** significant at 1%

The dependent variable is equal to 1 if respondent changed jobs between two consecutive months. Up to 6 potential transitions are observed for each individual. These estimates are for job changes from month t to t+1 conditional on being employed in the computer industry (SIC 35 and 36) in month t. Thus, from column 1, we see that we observe 2972 individuals over 8,966 month to month observations. 1.95% of these potential job changes resulted in actual job changes.

The coefficients in the table are derivatives, i.e. they reflect the impact of the variable on the probability of observing a job change between two consecutive months. Thus, in column 1, residing in San Jose increases the probability of job change by 1.2%, nearly doubling the base rate of job change for the sample.

Age Dummy Variables: < 25; <35, <45, < 55, < 65. In columns (2) and (5) chi square tests indicated that San Jose and California were jointly significant at better than the 1% level. In columns (3) and (6) chi square tests indicate that *San Jose, San Francisco, Los Angeles, and Orange County* were jointly significant at the 5% level. One cannot reject the hypothesis that these coefficients are jointly equal in magnitude either.

Table 2

Determinants of Month To Month Job Transitions Conditional on Being Employed in the Computer Industry Narrowly Defined (Census 322 and 342)

Variable [mean]	(1) Change Jobs [0.0196]	(2) Change Jobs [[0.0196]	(3) Change Jobs [0.0196]	(4) Change Jobs Within Industry [0.0083]	(5) Change Jobs Within Industry [0.0083]	(6) Change Jobs Within Industry [0.0083]	(7) Change Jobs [0.0196]	(8) Change Jobs Within Industry [0.0083]
San Jose [0.169]	0.018	0.006	0.023	0.009	0.005	0.010		
	(3.39)**	(1.20)	(3.96)**	(3.28)**	(1.64)	(3.48)**		
California [0.350]		0.013			0.004		0.017	0.008
		(2.93)**			(1.64)		(4.29)**	(3.58)**
San Francisco [0.020]			0.001			0.015		
			(0.11)			(1.94)		
Los Angeles [0.063]			0.018			0.002		
			(2.34)*			(0.56)		
Orange County [0.028]			0.01			0.006		
			(0.99)			(1.05)		
San Diego [0.034]			0.022			0.00		
			(2.12)*			(0.07)		
Massachusetts [0.093]							0.006	0.004
							(0.84)	(1.06)
Full-Time [0.965]	0.005	0.004	0.004	0.002	0.002	0.002	0.004	0.003
	(0.60)	(0.49)	(0.50)	(0.45)	(0.42)	(0.46)	(0.49)	(0.55)
US Citizen [0.732]	0.003	0.004	0.005	0.000	0.000	0.000	0.004	0.000
	(0.79)	(1.13)	(1.18)	(0.15)	(0.07)	(0.05)	(0.99)	(0.25)
Married [0.749]	-0.005	-0.004	-0.004	0.001	0.001	0.001	-0.004	0.001
	(1.35)	(1.18)	(1.16)	(0.46)	(0.53)	(0.71)	(1.14)	(0.70)
Post College Schooling [0.348]	-0.004	-0.004	-0.003	-0.003	-0.003	-0.003	-0.004	-0.004
	(1.18)	(1.06)	(0.94)	(1.71)	(1.64)	(1.68)	(1.07)	(1.77)
Year Fixed Effects 1994 - 2001	yes	yes	yes	yes	yes	yes	yes	yes
Month fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Age Dummy Variables	yes	yes	yes	yes	yes	yes	yes	yes
Observations	5773	5773	5773	5773	5773	5773	5773	5773
Number of Individuals	1961	1961	1961	1961	1961	1961	1961	1961

Absolute value of robust z-statistics in parentheses (with standard errors adjusted for clustering within individual). * significant at 5%; ** significant at 1%

The dependent variable is equal to 1 if respondent changed jobs between two consecutive months. Up to 6 potential transitions are observed for each individual. These estimates are for job changes from month t to t+1 conditional on being employed in the computer industry narrowly defined (Census 322 or 342) in month t. Thus, from column 1, we see that we observe 1961 individuals over 5773 month to month observations. 1.96% of these potential job changes resulted in actual job changes.

The coefficients in the table are derivatives, i.e. they reflect the impact of the variable on the probability of observing a job change between two consecutive months. Thus, in column 1, residing in San Jose increases the probability of job change by 1.8%, nearly doubling the base rate of job change for the sample.

Age Dummy Variables: < 25; <35, <45, < 55, < 65. In columns (2) and (5) chi square tests indicated that San Jose and California were jointly significant at better than the 1% level. In columns (3) and (6) In columns (3) and (6) chi square tests indicate that San Jose, San Francisco, Los Angeles, and Orange County were jointly significant at the 5% level. One cannot reject the hypothesis that these coefficients are jointly equal in magnitude either

Table 3

The Determinants of Month-to-Month Job Changes Conditional on *not* Being Employed in the Computer Industry (i.e. not being in SIC 35 or 36)

Variable [mean]	(1) Change Jobs [0.0244]	(2) Change Jobs [0.0244]	(3) Change Jobs [0.0244]	(4) Change Jobs [0.0244]	(5) Change Jobs [0.0244]
San Jose [.017]	0.002	0.004		0.002	0.003
	(0.78)	(1.23)		(0.59)	(0.72)
California [0.238]		-0.002	-0.002		-0.002
		(1.93)	(1.81)		(2.17)*
San Francisco [0.026]				0.000	
				(0.17)	
Los Angeles [0.126]				-0.003	
				(2.04)**	
Orange County [0.023]				-0.001	
				(0.39)	
San Diego [0.022]				-0.006	
				(2.17)**	
Location Quotient IT Sector					0.000
[1.91]					(0.06)
Location Quotient Own Industry					0.014
[0.984]					(1.64)
Massachusetts [.083]			-0.001		
			(0.78)		
Full-Time [0.871]	-0.016	-0.016	-0.016	-0.016	-0.016
	(12.44)**	(12.51)**	(12.48)**	-(12.5)**	(-12.47)**
US Citizen [0.842]	0.001	0.000	0.000	0.000	0.000
	(0.60)	(0.24)	(0.19)	(0.21)	(0.17)
Married [0.683]	-0.003	-0.003	-0.003	-0.003	-0.003
	(3.30)**	(3.42)**	(3.43)**	(3.39)	(3.46)
Post College Schooling [0.375]	-0.001	-0.001	-0.001	-0.001	-0.001
	(1.51)	(1.59)	(1.55)	(1.61)	(1.68)
Year Fixed Effects	yes	yes	yes	yes	yes
Month fixed effects	yes	yes	yes	yes	yes
Age Dummy Variables	yes	yes	yes	yes	yes
Observations	147183	147183	147183	147183	147183
Number of Individuals	42232	42232	42232	42232	42232

Absolute value of robust z-statistics in parentheses (with standard errors adjusted for clustering within individual).
* significant at 5%; ** significant at 1%

The dependent variable is equal to 1 if respondent changed jobs between two consecutive months. Up to 6 potential transitions are observed for each individual. These estimates are for job changes from month t to t+1 conditional on ***not*** being employed in the computer industry (SIC 35 and 36) in month t. Thus, from column 1, we see that we observe 42232 individuals with 147,183 month to month observations. 2.4% of these potential job changes resulted in actual job changes. The coefficients in the table are derivatives, i.e. they reflect the impact of the variable on the probability of observing a job change between two consecutive months. Thus, in column 1, residing in San Jose increases the probability of job change by 0.2%, less than 1/10th of the sample mean.

Table 3

The Determinants of Month-to-Month Job Changes Conditional on *not* Being Employed in the Computer Industry (i.e. not being in SIC 35 or 36)

Age Dummy Variables: < 25; <35, <45, < 55, < 65.

In columns (2) and (4) chi square tests indicated that San Jose and other California locations were not jointly significant.

Location Quotient IT is a ratio measure of the concentration of a cluster in a particular location relative to the national average. Thus Location Quotient IT > 1 indicates a higher than average concentration in that location in the year 2000 (see Cluster Mapping Project Institute for Strategy and Competitiveness for details).

Location Quotient Own Industry is an analogous variable constructed using our sample of college educated men. We first calculate the fraction of college educated men in an MSA who are in each two-digit census industry and then divide this by the average value for the entire sample. Thus Location Quotient Own Industry > 1 indicates an MSA which has a higher fraction of college educated employees in a census industry than the average across all MSA's.