

**Job-Hopping in Silicon Valley:  
The Micro-Foundations of a High Technology Cluster**

By

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

6/14/2004

## Abstract

In Silicon Valley's computer cluster, skilled employees move quickly and easily between competing firms. This job-hopping facilitates the reallocation of resources towards firms with superior technology, but also creates costly human capital externalities. Outside of California, employers can use non-compete agreements to reduce mobility costs, but non-compete agreements are unenforceable under California law.

Using new data on labor mobility we find higher rates of job-hopping for college-educated men in Silicon Valley's computer industry than in computer clusters located out of state. Mobility rates in other California computer clusters are similar to Silicon Valley's. Outside of the computer industry, California's mobility rates are no higher than elsewhere.

*JEL Classification* R12, L63, O3, J63; J48

## Introduction

The geographic clustering of firms is a ubiquitous, but poorly understood, feature of advanced economies.<sup>1</sup> Explanations for geographic concentration 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. In this paper we use a new source of data to examine empirically 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 the easy mobility of skilled employees among firms in Silicon Valley.

Annalee Saxenian (1994) was among the first to propose the idea that high rates of mobility were a source of agglomeration economies in Silicon Valley.<sup>2</sup> 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 incorporating the latest technological advances into modular components (Saxenian 2000). The modular nature of these components increased the rate of technical innovation by allowing rival component manufacturers the freedom to experiment with product design provided that their components conform to design rules that integrated components into the final product (Baldwin and Clark, 1997). Modularity also forced the various suppliers into a competition to build the

---

<sup>1</sup> 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.

<sup>2</sup> Some discussion of mobility preceded Saxenian’s work, see for example Angel 1989.

latest technology into components (Baldwin and Clark 1997, 2000).

The second key feature of the industrial organization of Silicon Valley was the rapid movement of tacit 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 mobility was further facilitated by the adoption of “open” operating systems (such as Unix) as well as modular component systems.

Innovation in the design of modular components by independent suppliers 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 (Saxenian 2000). The high rate of mobility among technical employees reinforced the benefits of modularity because skilled employees rapidly transferred from firms with inferior component designs to those with superior designs.

Job-hopping between companies creates the likelihood of knowledge spillovers because human capital acquired in one firm is employed in another. In high-technology industries these spillovers are likely to impose costs on employers (Gilson 1999). If the exit of employees with valuable tacit knowledge is costly for employers, individual companies can do better by taking advantage of the free flow of talent from other firms in the Valley while preventing the exit of their own employees. If so, then how could job-hopping be an equilibrium feature of Silicon Valley’s computer cluster? Gilson (1999) proposes a provocative set of answers to these questions. His analysis focuses on the “non-compete agreement”, the primary legal mechanism available to firms wishing to control the disposition of knowledge that employees acquire in the

course of their work. These employment agreements limit an employee's ability to find work with 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 reducing knowledge spillovers and hence the reallocation of labor resources towards the most effective designs. 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 other states.

Saxenian's and Gilson's accounts have captured much attention in management and policy circles. Their accounts are also interesting for economic theory because they describe a setting where strengthening property rights to investments in human capital can cause 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 a set of questions in the *Current Population Survey* to assess the rate of employer-to-employer mobility in Silicon Valley and elsewhere.<sup>3</sup> Using this data we find evidence that employees working in the computer industry cluster in Silicon Valley do indeed have higher rates of mobility than similar computer industry employees in other metropolitan areas having large information technology clusters. Secondly, and consistent with Gilson's

---

<sup>3</sup> 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.

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 features of the computer industry in a particular geographic location rather than features of the geographic area itself drive our findings.

Our paper proceeds in three parts. In the next section we discuss the literature on innovation and knowledge spillovers in industrial districts. In section three, we present our empirical results. The paper concludes with a brief discussion of the limitations of our analysis as well as issues for further research.

## **II. Agglomeration Economies, Human Capital Externalities, and Non-Compete Agreements**

In this section we position our discussion of Silicon Valley’s computer cluster in the context of the larger economic issue of human capital externalities.<sup>4</sup> We adapt Acemoglu’s (1996, 1997) model to specify how the innovation process in Silicon Valley improves the quality of technical innovation in the district while also creating high rates of labor mobility and costly human capital externalities. In this framework it is easy to show that individual employers can profit by writing and exercising non-compete agreements – even though these agreements will reduce the rate of technical innovation in the industrial cluster. Acemoglu’s model also makes clear that the phenomenon of costly knowledge spillovers is more general than Gilson’s (1999)

---

<sup>4</sup> Human capital externalities arise when investment in an individual agent’s skills creates benefits for other agents in the economy.

analysis of non-compete agreements would suggest. Indeed, it can arise even when the employer retains full control over valuable ‘trade-secrets’ or innovations and when no investments in firm-specific human capital are made.

Acemoglu (1997) posits a labor market where the surplus produced by the employment relationship is an increasing function of investments in general human capital and technology. Into this setting he adds a specific type of labor market friction: that some employment relationships are severed by random shocks *after* the human capital investments are made. In the reallocation of labor subsequent to these shocks, employees are randomly assigned to other employers with whom they must bargain for a share of the surplus created by *prior* investments in human capital and technology. The resulting labor market frictions have the effect of reducing the ex ante incentives to invest in general human. <sup>5</sup>

Acemoglu’s model is agnostic regarding the cause of the random shocks to employment relationships. For our purposes, however, it is useful to think of random shocks as the result of the stochastic nature of the innovation process within an industrial cluster.

Consider an industrial district with an exogenously determined number of risk neutral employees and component manufacturers. Each of the  $g$  component manufacturers has a Leontieff production function in which one employee produces a fixed output in period two based upon investments in product design and human capital made in period one. After period two the employee retires and the component production cycle starts again. To highlight the main point and simplify the analysis, we assume that the  $g$  employees and  $g$  component manufacturers are exactly enough to produce the number of components computer makers require.

In the innovation phase (period one) the employee works on a new component design and

---

<sup>5</sup> In a related paper, Acemoglu (1996), demonstrates that externalities resulting from these same labor market frictions can also produce social increasing returns in human capital.

also acquires tacit knowledge about the production, use and sale of components. As a result of the modular nature of components, this tacit knowledge will be useful at any component supplier. We denote the costs of acquiring tacit knowledge by  $c(t) = ct^2$ , where  $t$  is the amount of human capital acquired and  $c$  is a positive constant. The remaining upfront investment costs of developing a new design are captured by  $\delta$ .<sup>6</sup>

The technological value of the component designed in period one is denoted by variable  $a$ . Innovation is a random process and we represent  $a$  as a random variable drawn from a uniform distribution ranging from 0 to  $\gamma$ . Importantly for this setting (and for Acemoglu's model), the component supplier maintains property rights over its technology and investments in human capital complement the value of the technology. Following Acemoglu (1997) we represent the economic value of the firm's design by  $at$ .

Each of the  $g$  component suppliers conducts an independent design experiment in period one and the economic value of the design is realized in period two. The expected quality of the "best" technology that emerges from these simultaneous experiments can be expressed as the first-order statistic for the uniform distribution ranging 0 to  $\gamma$ :

$$(1) \quad \hat{a} = \frac{g\gamma}{g+1}.$$

An important implication of (1) is that the quality of the "best" invention increases the more component makers there are in the cluster, but there are diminishing marginal returns to cluster size. Tacit knowledge and technology are complementary. Thus, the economic value produced

---

<sup>6</sup> For our purposes, it is sufficient to assume that all firms make the same investment in technology. Acemoglu (1997) considers this case and then the more general case where firms' investment decisions are endogenous. In this general case, there can be multiple equilibria because the returns to a firm's technology investment depends on human capital investments elsewhere in the district and the returns to human capital investments depends on the proportion of firms who make large investments in technology.

in period two by an employee with tacit knowledge  $t$  working at the firm with the “best” technology in the industrial cluster is:

$$(2) E(t\hat{\alpha}) = \frac{t}{g} \left( \frac{g\gamma}{g+1} \right).$$

Each component supplier is equally likely, *ex-ante*, to produce the best innovation, so the probability of winning is  $1/g$ .

Modularity ensures that the firm with the “best” component design can sell its product to all the computer makers in the district, provided it can hire the  $g-1$  employees working at other suppliers to achieve the requisite scale of production in period two. The reallocation of skilled labor from inferior designs to the “best” design produces the job-hopping observed by Saxenian and others. This “winner take all” innovation contest also produces the sort of labor market imperfections highlighted by Acemoglu (1996,1997). The identity of the firm with the “winning design” is determined randomly *after* the design and human capital investments are made in period one. Each of the employees who move to the winning component supplier must therefore bargain with their new employer over their share,  $0 < \beta < 1$ , of the surplus produced by this new employment relationship.

Acemoglu (1997, p. 451) demonstrates that the unique equilibrium level of training investment is that which maximizes the total surplus in period two.<sup>7</sup> This is determined in our set-up by the following first-order condition:

$$(3) \quad (1+r)(2ct) = \frac{1}{g} \cdot \frac{g\gamma}{g+1} [(1-s) + s\beta] \Leftrightarrow \hat{t} = \frac{\gamma[1-s(1-\beta)]}{(g+1)(1+r)2c}; \quad s \equiv \frac{g-1}{g}; \quad 0 < \beta < 1.$$

---

<sup>7</sup> The key assumptions are that the firm and worker can write long-term contracts and utility is perfectly transferable between the firm and its first period employee. In addition, employees are assumed to receive an exogenously determined share,  $\beta$ , of the surplus produced by the employment relationship.

Notice that investments in tacit knowledge,  $\hat{t}$ , fall as  $(1-\beta)$  increases. This result is intuitive. When an employee moves to the winning firm in period two, the firm gets  $1-\beta$  of the surplus from investments made elsewhere in period one. This externality reduces incentives to invest in human capital. As Acemoglu emphasizes, this externality is not the result of investments in firm-specific human capital. Nor is it due to the difficulties of establishing property rights to trade secrets or inventions. Rather it is the result of labor market imperfections that result from the rapid and unpredictable reallocation of labor to firms with the winning designs.

Acemoglu (1997) argues that it is generally not possible to write a contract that internalized the human capital externality because such a contract would impose obligations on a party who was not part of the contract written in period one. Binding covenants not-to-compete, however, give the employer an alternative means of eliminating this externality.

Imagine that all employers in the industrial cluster had employees sign covenants not to compete in period one. By exercising these agreements, firms who do not produce the winning design in period one are able to prevent their employees from going to work at the firm with the best design. In this case, component suppliers would conduct their individual design experiments in period one and then sell their components to computer makers in period two. Maintaining the assumption that the quality of an innovation is drawn from a uniform distribution between 0 and  $\gamma$ , the expected quality of the average technology used in the district would be  $\gamma/2$ . Comparing this to equation (1), the reduction in the average quality of technology under non-compete agreements is:

$$(4) \Delta = \frac{g\gamma}{g+1} - \frac{\gamma}{2} = \gamma \frac{g-1}{2(g+1)} > 0 \text{ if } g > 1.$$

Thus as long as there is more than one component supplier; the expected quality of the technology used in the district will be higher in the absence of non-compete agreements ( $\Delta > 0$ ).

An important implication of (4) is that the negative effect of non-compete agreements on the technical quality of innovations is greatest when  $\gamma$  is large. This follows because the gains from having multiple simultaneous experiments in period one are greatest when the gains to innovation are both large and uncertain. Observers of the innovation process in computers argue that  $\gamma$  is especially large in this industry (Baldwin and Clark, 1994 and 2000; and Aoki, 2001).<sup>8</sup> It follows then that non-compete agreements will have a particularly pronounced effect on the quality of technical innovation in the computer industry.

While non-compete agreements depress the quality of the average technology in use in the district, they have the offsetting effect of eliminating human capital externalities by preventing inter-firm mobility. In the absence of mobility between period one and period two, employment relationships would support a level of human capital investment that satisfies the following first-order condition:

$$(5) \quad 2ct = \frac{\gamma}{2(1+r)} \Leftrightarrow t = \frac{\gamma}{4c(1+r)}.$$

The right hand side of (5) is the marginal cost of human capital investments and the left hand side is the expected marginal benefit reaped from this investment in period two at the expected level of technology quality,  $\gamma/2$ . Subtracting  $t$  in (5) from  $\hat{t}$  in (3) we find that the impact of non-compete agreements on human capital investments:

$$(6) \quad t - \hat{t} = \frac{\gamma}{4c(1+r)} - \frac{\gamma[1 - \theta(1 - \beta)]}{(g+1)(1+r)2c} > 0 \text{ if } g > 1.$$

Taken together, equations (4) and (6) indicate that Silicon Valley type industrial districts

---

<sup>8</sup> “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).

ought to look very different depending on the ability of employers to write binding non-compete agreements. In settings where such agreements are prohibited one should observe both higher rates of labor mobility and higher quality technology. The technology gains should be offset by human capital externalities that depress investment in tacit human capital.<sup>9</sup> Both these effects are likely to be heightened in computers because the gains from innovation are both large and uncertain, i.e.  $\gamma$  is large.

In the next section we use labor market data to test some predictions of our discussion of agglomeration economies and human capital externalities in Silicon Valley. Our approach differs from others who use labor market data to investigate human capital externalities. Moretti (2004) and Acemoglu and Angrist (2000), for example, use wage data to estimate how individual returns to education are influenced by the educational attainment of others in the labor market (defined respectively as cities or states).<sup>10</sup> This approach would not be appropriate in our setting because the effect of tacit knowledge spillovers on wages is theoretically ambiguous - depending in part on the amount of human capital investments firms choose to finance.<sup>11</sup> We focus our attention instead on evidence relating to the primary mechanism of tacit knowledge spillovers, inter-firm mobility.

---

<sup>9</sup> Since we observe computer clusters in states with and without binding non-compete agreements, one might expect that there exists conditions under which the surplus produced in one legal regime equals that produced in the other. In unpublished work, we show that this is indeed the case. Specifically we find values of  $g$  where the agglomeration economies derived from the rapid reallocation of labor to the best designs is exactly offset by the costs of human capital externalities.

<sup>10</sup> They reach different conclusion in part because their instrumenting strategies highlight different parts of the labor market (Moretti, 2004, p. 207)

<sup>11</sup> Acemoglu (1997, p. 453) points out that a variety of different wage profiles may emerge in his model of labor market frictions. In contrast to models of frictionless labor markets, Acemoglu also shows that firms have incentives to bear part of the cost of acquiring general human capital.

## Empirical Results

In this section we use new data on employee mobility to answer three questions that follow directly from the preceding analysis 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 in other states? Second, is there a “California” effect on the rate of inter-firm mobility for computer industry employees? Third, since the potential agglomeration economies Silicon Valley’s are manifest most strongly under special circumstances (i.e. when  $\gamma$  is large), 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? The preceding discussion suggests that the answers to these questions ought to be yes, yes and no.

### 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.<sup>12</sup> In addition, we focus our analysis on men to eliminate the potentially confounding effect of gender

---

<sup>12</sup> 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).

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 vity. 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.<sup>13</sup> 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.

14

### 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

---

<sup>13</sup> 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).

<sup>14</sup> 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  $(1-.0241)^{12} = 0.76$ . 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.

estimates of the probability that an individual in SIC 35 and 36 in month  $t$  changes employers before being re-interviewed in month  $t + 1$ .<sup>15</sup> 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.

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.

---

<sup>15</sup> 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 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.<sup>16</sup>

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 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,

---

<sup>16</sup> Of the 886 individuals in our sample who lived in California, 342 (under 40%) live in San Jose.

however, easily reject the hypothesis that *San Jose* and *California* are jointly insignificant ( $\chi^2(2) = 11.28$  and  $\text{Prob} > \chi^2 = 0.0035$ ). 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.<sup>17</sup> For this reason we interpret the absence of a *California* effect in columns (4)-(6) with some caution.

Columns (7) and (8) compare the “California” effect on mobility to the “Massachusetts” effect for each of our measures of employer to employer changes.<sup>18</sup> 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

---

<sup>17</sup> 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.

<sup>18</sup> 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.

*Massachusetts*.<sup>19</sup> Our conservative conclusion is that if a *Massachusetts* effect exists at all, we cannot be sure that it is different than the *California* effect.<sup>20</sup>

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 the analysis using a more narrow definition.<sup>21</sup> 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

---

<sup>19</sup> A  $\chi^2$  test of the hypothesis that *California* = *Massachusetts* in column (7) yields:  $\chi^2(1) = 0.50$  Prob  $> \chi^2 = 0.4799$ . The similar test for equation (8) yields  $\chi^2(1) = 0.32$  Prob  $> \chi^2 = 0.5699$

<sup>20</sup> 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.

<sup>21</sup> 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.

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  $1/10^{\text{th}}$  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  $\chi^2$  test does not allow us to reject the hypothesis that *California* and *San Jose* are jointly insignificant in column 3.<sup>22</sup> 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

---

<sup>22</sup>  $\chi^2(2) = 4.32$ .

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.<sup>23</sup> The second measure, *Location Quotient Own Industry*, estimates the density of employment in a respondent's industry and MSA relative to the national average.<sup>24</sup> Introducing these variables into a job change equation yields positive 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 gnificant.<sup>25</sup> 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

---

<sup>23</sup> This variable is constructed by dividing the fraction of MSA employment in its 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.

<sup>24</sup> 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. 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.

<sup>25</sup>  $\chi^2(2) = 2.89$ . 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.

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.

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.<sup>26</sup>

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

---

<sup>26</sup> 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.

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.<sup>27</sup>

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. 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.

---

<sup>27</sup> 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 our model of mobility

## References

- 1.) Acemoglu, Daron (1997) "Training and Innovation in an Imperfect Labour Market" The Review of Economic Studies, 64:3 p. 445-464.
- 2.) Acemoglu, Daron. (1996) "A Microfoundation for Social Increasing Returns in Human Capital Accumulation" Quarterly Journal of Economics. 111:3. p. 779-804,
- 3.) Acemoglu, Daron and Angrist, Joshua.(2000) "How Large Are Human-Capital Externalities? Evidence from Compulsory Schooling Laws." NBER Macroeconomics Annual 15: 1, p9-59
- 4.) Almeida, Paul and Kogut, Bruce., (1999) "Localization of Knowledge and the Mobility of Engineers in Regional Networks" Management Science. 45:7. p. 905-917.
- 5.) Angel, David P., (1989) "The Labor Market for Engineers in the U.S. Semiconductor Industry" Economic Geography. 65:2. p.99-112.
- 6.) Aoki, Masahiko, (2001) Toward a Comparative Institutional Analysis. The MIT Press : Cambridge, Massachusetts and London, England.
- 7.) Baldwin, Carliss Y. and Clark, Kim B., (1997) "Managing in an Age of Modularity" Harvard Business Review. p.84-93.
- 8.) Baldwin, Carliss Y. and Clark, Kim B., (2000) Design Rules: The Power of Modularity. MIT Press : Cambridge, Mass. and London, England.
- 9.) Cluster Mapping Project (2003), Institute for Strategy and Competitiveness, Harvard Business School
- 10.) Fallick, Bruce C. and Fleischman, Charles A., (2002) ""Employer to Employer Flows in the U.S. Labor Market" Working Paper. April 2002.
- 11.) 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.
- 12.) Moretti, Enrico (2004) "Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data" Journal of Econometrics. 121. p.175-212.
- 13.) Moen, Jarle, (2000) "Is Mobility of Technical Personnel A Source of R&D Spillovers?" National Bureau of Economic Research. No.7834. August 2000.
- 14.) Porter, Michael E., (2003) "The Economic Performance of Regions" Regional Science. 37:6&7. p.549-578.
- 15.) Porter, Michael E., (1998) "Clusters and The New Economics of Competition" Harvard Business Review. 76:6.
- 16.) 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.
- 17.) Saxenian, Annalee, (1994) Regional Advantage: Culture and Competition in Silicon Valley and Route 128. Harvard University Press : Cambridge, Massachusetts and London England.
- 18.) Saxenian, Annalee, (1996) "Inside-Out: Regional Networks and Industrial Adaptation in Silicon Valley and Route 128" Cityscape. 2:2. p.41-60.
- 19.) 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.

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]
<i>San Jose</i> [0.122]	0.012 (2.40)*	0.004 (0.80)	0.015 (2.87)**	0.009 (3.10)**	0.006 (1.77)	0.01 (3.31)**		
<i>California</i> [.302]		0.009 (2.40)*			0.003 (1.36)		0.012 (3.43)	0.006 (2.98)
<i>San Francisco</i> [.017]			0.002 (0.23)			0.015 (1.89)		
<i>Los Angeles</i> [0.069]			0.015 (2.43)*			0.004 (1.05)		
<i>Orange County</i> [0.030]			0.002 (0.30)			0.000 (0.09)		
<i>San Diego</i> [0.037]			0.015 (1.88)			0.00 (0.41)		
<i>Massachusetts</i> [0.089]							0.008 (1.48)	0.005 (1.24)
<i>Full-Time</i> [0.961]	0.002 (0.34)	0.002 (0.34)	0.002 (0.34)	0.005 (1.24)	0.005 (1.23)	0.005 (1.25)	0.002 (0.35)	0.005 (1.23)
<i>US Citizen</i> [0.748]	-0.002 (0.57)	-0.001 (0.25)	-0.001 (0.22)	-0.002 (0.76)	-0.001 (0.56)	-0.001 (0.58)	-0.001 (0.37)	-0.002 (0.82)
<i>Married</i> [.753]	-0.003 (0.80)	-0.002 (0.69)	-0.002 (0.69)	0.000 (0.21)	0.000 (0.16)	0.000 (0.06)	-0.002 (0.64)	0.000 (0.12)
<i>Post College Schooling</i> [.332]	0.001 (0.33)	0.001 (0.42)	0.001 (0.47)	-0.001 (0.50)	-0.001 (0.45)	-0.001 (0.53)	0.001 (0.36)	-0.001 (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)

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

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