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Job-Hopping in Silicon Valley: Some Evidence Concerning the Micro-Foundations of a High Technology Cluster

Bruce Fallick, Charles A. Fleischman, and James B. Rebitzer

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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

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Abstract

In Silicon Valley's computer cluster, skilled employees are reported to move rapidly between competing firms. If true, this job-hopping facilitates the reallocation of resources towards firms with superior innovations, but it also creates human capital externalities that reduce incentives to invest in new knowledge. Outside of California, employers can use non-compete agreements to reduce mobility costs, but these agreements are unenforceable under California law.

Until now, the claim of "hyper-mobility" of workers in Silicon has not been rigorously investigated. 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 the state. Mobility rates in other California computer clusters are similar to Silicon Valley's, suggesting some role for state laws restricting non-compete agreements. Outside of the computer industry, California's mobility rates are no higher than elsewhere.

JEL Classification R12, L63, O3, J63; J48

I. Introduction

The geographic clustering of firms is a ubiquitous, but poorly understood, feature of advanced economies.[1] 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 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 observe that high rates of mobility were a source of agglomeration economies in Silicon Valley.[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 incorporating the latest technological advances into modular components (Saxenian 2000). The modular nature of these components increased the rate of technical innovation in the region by enabling rival suppliers to pursue *simultaneous and independent* innovation strategies so long as the resulting component conformed with the design rules that integrated components into the final product (Baldwin and Clark, 1997).

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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.

The second key feature of the industrial organization of Silicon Valley was the rapid movement of technically sophisticated employees throughout the region. This 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, however, also creates the likelihood that knowledge acquired in one firm is employed in another. These knowledge spillovers can hamper innovation by reducing the rewards to investing in human capital. An implicit assumption in Saxenian's discussion of Silicon Valley is that the benefits of the agglomeration economies exceed the attendant losses due to knowledge spillovers. Gilson (1999) brought attention to this assumption and observed that high rates of mobility by knowledgeable employees were likely to impose non-trivial costs on employers. These costs may cause employers to take actions to limit job-hopping even when the social benefits of agglomeration economies exceed the costs. "Non-compete" agreements, according to Gilson, are the most important legal mechanism for reducing inter-firm mobility. These agreements limit an employee's ability to work with competing firms in a specific geographic area and for a specific 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 to inhibit costly mobility. California's legal system is exceptional in its treatment of non-compete agreements. Thus Gilson's hypothesis may explain why mobility (and agglomeration economies) should be unusually high in Silicon Valley. His hypothesis also suggests that similar high rates of mobility should be observed in computer clusters elsewhere in California, but not in other states.

Saxenian's and Gilson's accounts have captured much attention in management and policy circles. Unfortunately data limitations have, until now, precluded direct empirical examination of some 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 exploit little-used data from the *Current Population Survey* to measure the rate of employer-to-employer mobility in Silicon Valley and elsewhere.[3] We find, first, 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. Second, and consistent with Gilson's hypothesis that California state law is important for 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 interaction between features of the computer industry and those of a particular geographic location, rather than features of the location alone, drive our findings.

The approach we take differs in two ways from other empirical studies of agglomeration economies and human capital externalities.[4] First, we focus on employee mobility within a labor

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3 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.

4 Acemoglu and Angrist (2000) and Moretti (2004) study how returns to education vary with the educational attainment of *others* in a geographically specified labor market (defined respectively as cities or states).Moretti finds some evidence in favor of the existence of human capital externalities while Acemoglu and Angrist's results offer less support. Moretti suggests that these authors reach different conclusion in part because their instrumenting strategies highlight

market rather than on the returns to education. We adopt this approach because inter firm mobility is more closely related to the agglomeration economy conjectured to operate in Silicon Valley.[5] Secondly, we examine our variable of interest for a *specific industry* within geographically specified labor markets. This industry focus is important because the agglomeration economies we analyze are likely to be more important in industries like computers where the gains from innovation are large but also uncertain.

Our paper proceeds in three parts. In the next section, we discuss the relationship between the literature on innovations in computer clusters and recent theoretical analyses of human capital externalities and agglomeration economies. This discussion helps clarify our empirical hypotheses. 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. Human Capital Externalities, Agglomeration Economies, and Non Compete Agreements

In this section we discuss the relationship between the literature on innovation in computer clusters and recent theoretical analyses of human capital externalities and agglomeration economies. We rely heavily upon Acemoglu's (1997) analysis of innovation in a labor market with inefficient job search. Acemoglu's model establishes a number of important results regarding knowledge spillovers.[6] It also offers a parsimonious framework for

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different parts of the labor market (Moretti, 2004, p. 207).

5 Indeed the model of agglomeration economies and human capital externalities we rely on does not make clear predictions about wages (see Acemoglu 1997, p. 453).

6 He finds, for example, that investments in general skills will be suboptimal and that part of the costs might be borne by employers (Acemoglu, 1997). In a related paper (Acemoglu 1996) he also uses this framework to describe new microfoundations for increasing returns to human capital accumulation.

understanding how modular design and "job hopping" can produce external economies of scale in a computer cluster.

<u>*Investments in Human Capital and Human Capital Externalities*</u>*:* Acemoglu (1997) posits a two period employment relationship in which a single employee uses a firm's technology to produce a product. Investments are made in human capital in period one and the product is produced in period two. The value of the product produced in period two is $y+at$, where y is a positive constant, a is the quality of the firm's technology, and t is the level of general human capital investments made in period one.[7] An important feature of this specification is that technology and human capital investments are complementary, the returns to human capital investment increase the higher the quality of technology.

Acemoglu introduces a specific type of labor market imperfection into this setting: that there is a probability, s, that the employment relationship will be severed by random shocks *after* human capital investments are made in period one. In the arbitrary reallocation of labor subsequent to these shocks, the affected employees each find work at a different firm in period two. Conversely the employers affected by these shocks will also have new employees in period two. In these newly formed employment relationships, employers are assumed to have sufficient bargaining power to gain a share of the surplus created by their current technology and *prior* investments in employee human capital.[8] The fact that some employers in period two can benefit from human capital investments made in a different employment relationship in period one creates a human capital externality that reduces ex-ante incentives to invest in general human

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[7] The economy has an exogenously determined number of risk neutral employees and component manufacturers. Each of the component manufacturers has a Leontieff production function in which one employee produces a fixed output in period two based upon technology and investments in human capital made in period one.

[8] Acemoglu also considers a case with infinite number of periods, but that is not necessary for our purposes.

capital.

More formally, Acemoglu (1997 p. 451, equation 2) writes the ex ante total surplus produced by each employment relationship as:

$$(1)\quad TS = \frac{(1-s)(y+at)+s[\beta(y+at)+(1-\beta)(y+aE(\tilde{t}))]}{1+r} - c(t)$$

The cost of acquiring knowledge, c(t), is a convex function of t, the amount of general human capital acquired. These costs are incurred in period one while the benefits from the human capital investments arrive in period two (hence the discounting). Each employment relationship stays intact with probability (1-s) and produces $y + at$. Employment relationships are severed with probability s and in this case the separated employee gains only a proportion, $0 < \beta < 1$, of the surplus produced by the second period employer's technology and their own human capital. The expected output for each of these new, period two, employment relationships is $y + aE(\tilde{t})$, where $E(\tilde{t})$ is the expected human capital of employees displaced by the random shock.

Acemoglu (1997, proposition 2 p. 451) demonstrates that in this setting there is a unique equilibrium, in which the total surplus described in (1) above is maximized. Thus, all pairs in period one choose a level of training, $\hat{t}$, that satisfies the first-order condition $(1+r)c' = a[(1-s) + s\beta]$. If we simplify equation (1) by specifying that the cost of investment function $c(t) = ct^2$, then we can use this result to derive an explicit expression for investments in human capital:

$$(2)\qquad \hat{t} = \frac{a[(1-s)+s\beta]}{2c}$$

Notice that $d\hat{t}/d\beta > 0$ and $d\hat{t}/ds < 0$ so long as $\beta < 1$. These results make intuitive sense. As β increases, employees dislocated in period two can recoup a greater return on their human capital and this increases investments in human capital. Conversely, ex-ante incentives to invest in human capital are reduced when the probability of separation increases. From (2) the value produced by each employment relationship in period two is:

$$(3) \qquad y + a\hat{t} = y + \frac{a^2[(1-s)+s\beta]}{2c}$$

<u>*Introducing Silicon Valley Type Agglomeration Economies*</u>: [9] According to Saxenian (1994) and Baldwin and Clark (2000), the technological dynamism in the computer industry stems in part from their modular design. Modularity enables rival suppliers to pursue *simultaneous and independent* innovation strategies so long as the resulting components conform to the design rules that integrate components into the final product. Computer makers can then pick the best of these for use in their products.

A simple way to introduce modularity into Acemoglu's set-up is to allow it to shape the technology variable, *a*, in equation (3). More specifically we assume that innovation is a random process and the quality of the technology that emerges, *a*, is determined by a random variable drawn from a uniform distribution ranging from 0 to γ. The larger is γ, the greater is the expected return to innovative activity and the greater is the variation in outcomes. If there are *g* component makers in the industrial cluster, the expected value of the "best" design to emerge from the component makers is the first order statistic for the uniform distribution ranging 0 to γ:

$$(4) \qquad a = \frac{g\gamma}{g+1} \text{ with } g \geq 1.$$

It is clear from (4) that the value of the best technology increases with the number of component

[9] Our discussion focuses on the sorts of agglomeration economies highlighted by observers of the computer industry. There are, of course, many other potential sources of agglomeration economies. Rotemberg and Saloner (2000) consider the role that clusters play in inducing *industry-specific* human capital investments. They argue that suppliers will be reluctant to undertake industry-specific investments if they anticipate only one local customer for their product. The fear that a single customer may exert monopsony power is reduced, however, if a number of customers locate in an area. The result, in our context, is computer cluster with many computer makers and many component suppliers.

suppliers in the cluster, g, although there are diminishing marginal returns to g. Note as well that a is also increasing in γ.

For the innovation process described in (4) to be a source of agglomeration economies, it needs somehow to be localized (Rotemberg and Saloner 2000). This is where job-hopping enters the picture. The firm with the "best" component design can sell its product to all the computer makers in the district, provided it hires enough of the employees working at other component makers to achieve the requisite scale of production. Since employees change jobs most easily when they do not have to move their households, the innovation advantages of modularity and job-hopping are best realized when the g component makers locate in a particular location. [10]

This argument is not sufficient, however, to establish that job-hopping is a source of agglomeration economies. The random process by which firms discover key innovations and the subsequent reallocation of labor to those firms produces exactly the sort of random shocks that form the basis of Acemoglu's analysis. We know from (3) that increases in s, the probability that employment relationships are disrupted, has ceteris paribus, the effect of reducing incentives to invest in human capital. Thus for job-hopping to be a source of agglomeration economies, we need to establish the conditions under which increasing the value of the technology, a, offsets the potential losses due to reduced incentives to invest in general human capital, t.

In an appendix to this paper, we consider more formally the conditions under which modularity and job-hopping produce agglomeration economies. We find, not surprisingly, that so long as the human capital externalities from job hopping are not "too large", i.e. so long as parameter β in equation (3) is above some minimal threshold, the gains from allocating

10 Saxenian's (1994) discussion also highlights another externality: the innovations that result when job-hopping computer maker employees with valuable tacit knowledge interact with employees at component makers. These constitute what Acmoglu and Angrist (2000) term "non-pecuniary externalities. We simplify our analysis by not formally modeling this aspect of spillovers.

employees to firms with the best technology ex-post exceed the losses due to reduced human capital investments ex-ante.

We also find that the magnitude of the agglomeration economies produced by job-hopping increases with parameter γ. This makes intuitive sense: the advantages of having more independent and simultaneous experiments are greatest when the gains to innovation are both large and uncertain. Observers of the innovation process in computers argue that γ is especially large in this industry (Baldwin and Clark, 1994 and 2000; and Aoki, 2001).[11]

However, even if job-hopping would benefit the industrial cluster as a whole, it may remain individually optimal for each firm to attempt to limit the mobility of its own employees. The lower the cost of imposing such limitations, the less likely a job-hopping equilibrium is to be observed.

Non-Compete Agreements: Gilson's original discussion of non-compete agreements in high technology districts emphasized their importance for firms seeking to retain control over trade secrets and proprietary innovations should employees move to competitors. Acemoglu's analysis makes clear, however, that the costs of knowledge spillovers can be substantial even when all human capital is general and when firms retain full control over their trade secrets and technology. The source of these costs is clear. Job hopping reduces the incentives to invest in human capital ex ante and this reduces the value of the firm's product. To the extent that binding non-compete agreements reduce the probability that an employee will be working at new employers in the future, these covenants can induce higher levels of general human capital

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11 "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).

investment, *t*. In this sense, covenants not to compete offer a legal mechanism to reduce the cost of human capital externalities resulting from job-hopping.[12] Firms may find it individually desirable to exercise these agreements even if this reduces the technological vitality of the industrial cluster. And if such covenants are a more cost-effective way of inhibiting mobility than are other methods (such as deferred compensation schemes), then we might expect to see lower mobility in clusters where non-compete agreements are available.

III. Empirical Results

In this section we marshal little-used data on employee mobility to answer three questions that follow directly from the preceding analysis. First, is the inter-firm mobility of employees in the computer industry indeed higher in Silicon Valley than in other IT clusters in other states with non compete agreements? Second, is there a "California" effect on the rate of inter-firm mobility for computer industry employees, as one might expect if the agglomeration economies are due to features of California state law? Third, since the conjectured agglomeration economies in Silicon Valley are manifest most strongly under special circumstances (i.e. when γ 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 discussion in the preceding section suggests that the answers to these questions ought to be yes,

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[12] Acemoglu (1997) argues that human capital externalities resulting from random shocks and imperfect job search cannot be internalized by conventional contracts that require the period two employers to compensate either of the parties to the employment relationship in period one. He reasons, correctly, that such a contracting strategy is unworkable because the identity of the ultimate employer in period two is not known prior to the random shock. How could a court uphold a contract that imposes obligations on a third party who was not party to the original agreement? Covenants not-to-compete can, however, circumvent these contractual limitations because they simply restrict the ability of employees to work for competing firms in a specific location for a specific period of time. The future employer needn't be party to the agreement.

yes and no.

Data:

The data we use in our analysis come from a relatively new feature of the Current Population Survey (CPS). With the redesign of the CPS in January 1994, the Census Bureau sought to reduce the number of questions asked afresh to respondents 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 "dependent interviewing" approach allowed for the collection of the mobility data we use in this study. If a respondent is reported employed in one month and was also reported 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).

The CPS data on month-to-month mobility are well suited for studying agglomeration economies. 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 their employers over longer stretches of time. 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. (See Fallick and Fleischman 2004 for a fuller description of the data.)

The computer industry agglomeration economies that motivate our study emphasize the mobility of 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.[13] 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 in our sample period (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 for each individual ranges from 1 to 6 with the median being 3.[14] Of the individuals in our sample, 3,768 (or 7.84%) were observed to have changed employers at

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13 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; Philadelphia; Houston; and Denver. Details on the identification of clusters are in Porter (2003). We define Silicon Valley as being in the MSAs of San Jose, San Francisco and Oakland, but our results also hold if we define Silicon Valley as San Jose only.

14 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. Thus each individual can have 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' initial 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. Others are lost to nonresponse or other data problems. After taking account of factors (1)-(3) above, the number of individuals lost from the sample 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 (2004).

least once. The monthly rate of employer-to-employer job change is 2.41 percent.[15]

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 Table 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 $t+1$.[16] 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. For continuous variables, the probit estimates are presented as derivatives evaluated at the mean of the right-hand side variables; for dummy variables the estimates are presented as the difference in probabilities as the value of the variable switches from 0 to 1.

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15 If we assume that 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 $(1-.0241)^{11} = 0.76$. This figure may appear high, but it is worth noting that the hazard of exiting a firm is not constant. Our confidence in the CPS mobility data is further strengthened by the fact that it produces estimates that match well with data from the Longitudinal Employer-Household Dynamics (LEHD) program at the Census Bureau. The LEHD uses tax records from the unemployment insurance program that constitute a near universe-count of on-the-books wage and salary employment in the participating states. The LEHD matches these records over time by employer and employee. We tabulated data from 20 of the 50 states, representing about 55 percent of total employment in the U.S., for a period from late-1995 through mid-2003. (The data are available, state by state, at "http://lehd.dsd.census.gov".) Over this period, the average quarterly separation rate and accession rate from the LEHD, as a percent of employment, were 20.1% and 20.6%, respectively. The comparable rates from our matched CPS data are 19.9% and 19.7%, respectively.

16 SIC 35 and 36 constitute a conventional but overly broad definition of the computer industry: Industrial and Commercial Machinery and Computer Equipment; and Electronic and Other Electrical Equipment and Components, Except Computer Equipment.

Thus the 0.008 coefficient on the variable *Silicon Valley* in column 1 indicates that living in Silicon Valley increases the rate of employer to employer job change by 0.8 percentage point. This effect is both statistically and behaviorally significant -- suggesting employer-to-employer mobility rates are more than 40% higher than the sample average. On this basis, the impression of hyper-mobility that Saxenian noted in studies of the late 80s and early 90s appears to have persisted in Silicon Valley throughout the 1990s.

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 *Silicon Valley* falls to zero 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 1.1 percentage points above the sample mean (z score 2.66) – an increase of 56 percent. These results are consistent with Gilson's hypothesis regarding California law: The Silicon Valley effect on mobility appears to run throughout the state's computer clusters.

Column 3 of Table 1 estimates job change rates separately for each of the MSAs in California having IT clusters. Employees in the computer industry residing in *Los Angeles* and *San Diego* had mobility rates virtually identical to *Silicon Valley.* 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.

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 in 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 *Silicon Valley* is 0.008 (z score = 3.27), suggesting that this measure of job change is nearly 90% higher in Silicon Valley than the sample mean. Column (5) introduces the California dummy. The coefficient on this variable is positive, but small in magnitude (0.002) and imprecisely measured (z = 0.880). As importantly, the coefficient on *Silicon Valley* falls by twenty-five percent and also becomes statistically insignificant at conventional levels. One can, however, easily reject the hypothesis that *Silicon Valley* and *California* are jointly insignificant ($\chi^2(2) = 11.28$ and Prob > $\chi^2 = 0.0035$). Taken together, these results suggest that given the smaller number of employer-to-employer moves within the computer industry (as we define it), 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 large and positive coefficient on *Silicon Valley* (0.009 and significant at the 1% level). 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 *Silicon Valley* than in computer industries located elsewhere. These results do not offer support for Gilson's hypothesis -- heightened mobility seems to be concentrated in

Silicon Valley , 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 rates of job hopping in Silicon Valley's 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 Silicon Valley, 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 Silicon Valley 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.[17] 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"

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[17] In a private communication with one of the authors, 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.

effect for each of our measures of employer to employer changes.[18] 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). In both columns, however, the *Massachusetts* coefficient is imprecisely measured 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*.[19] Our conservative conclusion is that if a *Massachusetts* effect exists at all, we cannot be sure that it is different than the *California* effect.[20]

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

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18 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.

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

20 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. In other unpublished results we re-estimated equation (7) using a complete set of state dummies with California as the omitted state. We find that 11 out of 15 dummies had negatively signed coefficients, a few significantly so, and none had significantly positively signed coefficients. Although many of the individual coefficients were not statistically significant, the entire set of dummies was highly significant.

the analysis using a narrower definition.[21] 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 of 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 *Silicon Valley* 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. Column 2 introduces a California dummy variable into the equation. The coefficient on *California* is also small, but negative and statistically significant while the *Silicon Valley* coefficient is positive and significant. The mobility differential for being in Silicon Valley is the

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[21] 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 have been excluded.

sum of these coefficients or 0.001. This differential is both small and not statistically different from zero ($\chi^2(1) = 0.46$). Similarly when we disaggregate the *California* effect by introducing 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 *Silicon Valley*. Indeed rates of job-hopping appear to be lower in Los Angeles and San Diego than elsewhere in the nation. Taken together, the 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. 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.[22] The second measure, *Location Quotient Own Industry*, estimates the density of employment in a respondent's industry and MSA relative to the national average.[23] Introducing these variables into a job change equation yields positive coefficients that are very imprecisely measured considering the size of

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[22] 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.

[23] 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.

the sample. Thus we cannot reject the null hypothesis that either *Location Quotient IT* or *Location Quotient Own Industry* have no effect on mobility. We also cannot reject the hypothesis that these coefficients are jointly insignificant.[24] 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 uses new data to compare the inter-firm mobility of college educated male employees in Silicon Valley's computer industry to similarly educated employees working in the computer clusters in other cities. The hyper mobility we document for Silicon Valley's computer cluster is consistent with Saxenian's account of agglomeration economies there: frequent job-hopping facilitates the rapid reallocation of resources towards firms with the best innovations. Our finding of a "California" effect on mobility lends support to Gilson's hypothesis that the unenforceability of non compete agreements under California state law enhances mobility and agglomeration economies in IT clusters. Our final finding, that heightened mobility is feature of California's computer industry but not of other California industries, is consistent with claims that external economies of scale are particularly important for the innovation process in the computer industry.

This interpretation of our results must be qualified by the limitations of our data. We observe only the movement of employees between firms and the correlation of these mobility rates with industry and location. Thus, we cannot rule out the hypothesis that rapid employee mobility may be the result of some unobserved features of computer firms in California rather than the agglomeration economy we posit. In addition, we do not observe employment contracts

[24] 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.

and therefore have no direct evidence that the “California” effect on mobility 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.

Finally, our analysis suggests that agglomeration economies observed in Silicon Valley’s IT cluster ought *not* to be a general economic phenomenon. Rather they should arise in settings, like computers, where the gains from new innovations are both large and uncertain. 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.

Appendix 1

Consider an industrial district with an exogenously determined number of risk neutral employees and component manufacturers. Each of the *g* component manufacturers has an identical Leontieff production function in which one employee produces a fixed output in period two based upon the technology the firm controls and human capital investments 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 demand for components is fixed and that the *g* employees and *g* component manufacturers are exactly enough to produce the number of components computer makers require.

In these circumstances, 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. Since all firms are ex-ante equally likely to discover the "best" design and since there can only be one "best" design, the probability that any component supplier finds it is 1/*g*. Thus, s¸ probability that any of the employment relationships will be severed prior to production in period two is 1- (1/g). Substituting equation (4) and this expression for *s* into equation (3), the value of production in period two becomes:

$$\text{(A1)} \qquad y + \hat{a}t = y + \frac{\gamma g}{2c(1+r)(g+1)}\left(\frac{1}{(g+1)} + \beta\frac{(g-1)}{(g+1)}\right) \text{ for } g \geq 1$$

Agglomeration economies exist when $d(y+\hat{\alpha}t)/dg > 0$. Taking the derivative of $\hat{a}t$ with respect to *g* we find

$$\text{(A2)} \qquad \frac{d(y+\hat{a}t)}{dg} = \frac{\gamma}{2c(1+r)}\frac{\beta(3g-1)-(g-1)}{(g+1)^3} > 0 \text{ if and only if } \beta > (g\text{-}1)/(3g\text{-}1)$$

The conditions under which $d(y+\hat{\alpha}t)/dg > 0$ reflect the opposing influence of agglomeration economies and human capital externalities. So long as the externalities do not reduce incentives to investment in knowledge too badly, i.e. so long as β is above some threshold, the gains from allocating employees to firms with the best technology ex-post exceed the losses due to reduced human capital investments ex-ante. Because the marginal innovation benefit of adding more component suppliers to the cluster declines in *g*, the minimum threshold value of β increases with *g*. The results in A2 also demonstrate that the gains from agglomeration economies are greatest when γ is large. This follows because the advantages of having multiple independent and simultaneous experiments are greatest when the gains to innovation are both large and uncertain.

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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)
	Change Jobs	Change Jobs	Change Jobs	Change Jobs Within Industry	Change Jobs Within Industry	Change Jobs Within Industry	Change Jobs	Change Jobs Within Industry
Variable [mean]	[0.0195]	[0.0195]	[0.0195]	[0.009]	[0.009]	[0.009]	[0.0195]	[0.009]
Silicon Valley [0.166]	0.008	0.000	0.011	0.008	0.006	0.009		
	(2.02)*	(0.100)	(2.54)*	(3.27)**	(1.750)	(3.37)**		
California [.302]		0.011			0.002		0.012	0.006
		(2.66)**			(0.880)		(3.43)**	(2.98)**
Los Angeles [0.069]			0.015			0.004		
			(2.41)*			(1.050)		
Orange County [0.030]			0.002			0.000		
			(0.280)			(0.090)		
San Diego [0.037]			0.015			0.002		
			(1.860)			(0.420)		
Massachusetts [0.089]							0.008	0.005
							(1.48)	(1.24)
Full-Time [0.961]	0.00	0.00	0.003	0.01	0.005	0.005	0.002	0.005
	(0.37)	(0.37)	(0.36)	(1.24)	(1.23)	(1.24)	(0.35)	(1.23)
US Citizen [0.748]	-0.003	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.002
	(0.74)	(0.34)	(0.39)	(0.85)	(0.70)	(0.71)	(0.37)	(0.82)
Married [.753]	-0.003	-0.002	-0.002	0.000	0	0	-0.002	0
	(0.82)	(0.71)	(0.73)	(0.19)	(0.17)	(0.19)	(0.64)	(0.12)
Post College Schooling [.332]	0.001	0.00	0.00	(0.00)	-0.001	-0.001	0.001	-0.001
	(0.30)	(0.47)	(0.44)	(0.56)	(0.51)	(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 Silicon Valley increases the probability of job change by 0.8%, roughly forty percent above the base rate of job change for the sample.

In columns (2) and (5) chi square tests indicated that Silicon Valley and California were jointly significant at better than the 1% level. In columns (3) and (6) chi square tests indicate that *Silicon Valley 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.

The varialbe *Silicon Valley* includes the cities of San Jose, San Francisco and Oakland California. Age dummies are: < 25; <35, <45, < 55, < 65 years old

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]
Silicon Valley [0.224]	0.014	0.002	0.019	0.008	0.006	0.009		
	(3.14)**	(0.32)	(3.79)**	(3.55)**	(1.79)	(3.67)**		
California [0.350]		0.015			0.002		0.017	0.008
		(3.04)**			(0.91)		(4.29)**	(3.58)**
Los Angeles [0.063]			0.019			0.002		
			(2.39)*			(0.64)		
Orange County [0.028]			0.011			0.006		
			(1.03)			(1.12)		
San Diego [0.034]			0.023			0		
			(2.17)*			(0.01)		
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)	(0.50)	(0.50)	(0.43)	(0.42)	(0.42)	(0.49)	(0.55)
US Citizen [0.732]	0.002	0.004	0.004	0.000	0.000	0	0.004	0.000
	(0.59)	(1.00)	(0.98)	(0.25)	(0.12)	(0.09)	(0.99)	(0.25)
Married [0.749]	-0.005	-0.004	-0.005	0.001	0.001	0.001	-0.004	0.001
	(1.38)	(1.19)	(1.21)	(0.47)	(0.51)	(0.55)	(1.14)	(0.70)
Post College Schooling [0.348]	-0.005	-0.004	-0.004	-0.003	-0.003	-0.003	-0.004	-0.004
	(1.26)	(1.02)	(1.03)	(1.81)	(1.75)	(1.73)	(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 Silicon Valley increases the probability of job change by 1.4%, roughly 70% above 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 Silicon Valley 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 Silicon Valley, Los Angeles, and Orange County were jointly significant at the 1% 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]
Silicon Valley [0.067]	0.002	0.004	0.001		0.004
	(1.05)	(2.16)*	(0.69)		(1.79)
California [0.238]		-0.003		-0.002	-0.003
		(2.51)*		(1.81)	(2.65)
Los Angeles [0.126]			-0.003		
			(2.00)*		
Orange County [0.023]			-0.001		
			(0.37)		
San Diego [0.022]			-0.006		
			(2.16)*		
Location Quotient IT Sector					-0.00002
[1.91]					(0.06)
Location Quotient Own Industry					0.013
[0.984]					(1.53)
Massachusetts [.083]				-0.001	
				(0.78)	
Full-Time [0.871]	-0.016	-0.016	-0.016	-0.016	-0.016
	(12.42)**	(12.49)**	(12.49)**	(12.48)**	(12.46)**
US Citizen [0.842]	0.001	0.000	0.000	0.000	0.000
	(0.62)	(0.15)	(0.22)	(0.19)	(0.10)
Married [0.683]	-0.003	-0.003	-0.003	-0.003	-0.003
	(3.27)**	(3.39)**	(3.38)**	(3.43)**	(3.42)**
Post College Schooling [0.375]	-0.001	-0.001	-0.001	-0.001	-0.001
	(1.51)	(1.63)	(1.61)	(1.55)	(1.70)
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
Observed/Potential job changes	0.024412	0.024412	0.024412	0.0232	0.0232

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 *Silicon Valley* 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 column (2), the mobility differential from living in Silicon Valley is the sum of the coefficients on *Silicon Valley* and *California*. One cannot reject the hypothesis that the sum of these coefficients is 0 (χ^2=0.46).

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.